ESSAYS IN LABOR AND DEVELOPMENT ECONOMICS

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Abstract

The dissertation consists of three independent explorations of labor market dynamics in developing countries. I first investigate how minimum wages affect employment and investment decision of firms in India and how they can lead to accelerated automation and offshoring. Then, I investigate how managers of garment production lines in India's largest ready-made garment producer establish informal agreements to deal with worker absenteeism shocks. Finally, I study how Indonesian households learn about their productivity in different sectors of the economy and show that they often spend years, if not decades, in sectors where they are less productive which depresses their earning potentials, but they converge to their most productive sector over time. In the first chapter, "*Effect of Minimum Wages on Automation and Offshoring Decisions of Firms: Evidence from India*", I study the effect of India's local minimum wages on the production structure of firms in the formal economy. I compile data on the country's numerous minimum wages which vary at the state, year, and industry level, and show that changes to these wages have important effects on firm-level capital investment and employment of different types of employees. The effects depend on the

firms' ability to automate and offshore certain tasks. Using a difference-in-difference approach, I show that firms in the average industry, that is, firms in industries neither intensive in routine nor offshorable tasks, continue to invest in machinery and computers at a rate of 8% per year following a minimum wage hike. However, they substitute payroll workers with managers and contract workers less likely to be bound by the minimum wage. Firms in industries intensive in routine tasks that are easier to automate invest 6.1% more in machinery and 4% more in computers, at the expense of payroll workers. Firms in industries intensive in tasks easier to do remotely continue to invest in machinery and computers, but the rate of investment in computers falls by 6.2% following a minimum wage hike, and payroll worker employment falls as well. This suggests that some tasks that combine workers and computers, like data analysis, may be offshored. These results support the predictions of a task-based production model, and indicate that minimum wages have a strong effect on the structure of production at the firm level, leading some towards increased rates of automation and offshoring. In the second chapter, "*Absenteeism, Productivity, and Relational Contracts Inside the Firm*", joint with Achyuta Adhvaryu, Anant Nyshadham, and Jorge Tamayo, we study relational contracts among managers using unique data that tracks transfers of workers across teams in Indian ready-made garment factories. We focus on how relational contracts help managers cope with worker absenteeism shocks, which are frequent, often large, weakly correlated across teams, and which substantially reduce team productivity. Together these facts imply gains from sharing workers. We show that managers respond to shocks by lending and borrowing workers in a manner consistent with relational contracting, but many potentially beneficial transfers are unrealized. This is because managers' primary relationships are with a very small subset of potential partners. A borrowing event study around main trading partners' separations from the firm reinforces the importance of relationships. We show robustness to excluding worker moves least likely to reflect relational borrowing responses to idiosyncratic absenteeism shocks. Counterfactual simulations reveal large gains to reducing costs associated with forming and maintaining additional relationships among managers. In the last chapter, "*Learning, Selection, and the Misallocation of Households Across Sectors*", joint with Teresa Molina and Anant Nyshadham, we study the role of labor misallocation (i.e., suboptimal sorting of households across sectors) in explaining low productivity in developing countries. We estimate a generalized earnings equation with dynamic correlated random coefficients, allowing households to learn about their relative productivity across the agricultural and non-agricultural sectors. Estimates show that households sort across sectors on comparative advantage, but learn and converge slowly over time, with many households spending substantial time in a suboptimal sector. Roughly 33% of households are misallocated to start, earning 64% less on average than they could have if they were properly sorted across sectors. Our approach nests several alternative models which can be ruled out, including those without dynamics and/or heterogeneity in relative productivity across sectors. We also evaluate alternative interpretations for the dynamic sorting we observe in the data such as saving out of financial constraints and skill accumulation or learning by doing.

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Chapter I

Effect of Minimum Wages on Automation and Offshoring Decisions of Firms

1 Introduction

Rising wages in an industry can lead firms to seek labor-saving alternatives to their existing modes of production. As a result, firms in that industry may innovate, invest in capital-intensive technologies, and/or offshore part of their production (Acemoglu (2010), Grossman and Rossi-Hansberg (2008), Hornbeck and Naidu (2014)). Doing so may expand firms' production capacity, and alter the importance of different industries in the share of aggregate output, thus affecting the structural transformation of nations (Acemoglu and Guerrieri (2008)).[1] In this essay, I focus on Indian firms' decisions to automate and offshore their production in response to rising minimum wages.[2] Most research on minimum wages has focused on aggregate employment effects, and has produced mixed results.[3] However, the role of minimum wages as instru-

[1]As economies develop, they tend to progress through a structural transformation in which there is, first, a relative reallocation of consumption and production away from agriculture, and towards manufactured goods. This is followed by a reallocation away from manufactured goods to services.

[2]Offshoring occurs when firms move some operations to another country (e.g. when GM moves its car assembly lines to Mexico). This is different from outsourcing where firms contract another party for a specific function (e.g. when GM hires a firm to produce molds for certain car parts).

[3]For example see Neumark and Wascher (2007), Dube et al. (2010), Cengiz et al. (2019), and Neumark et al. (2014) for a review of research on developed countries, and Neumark et al. (2006), Bell (1997), as well as Betcherman (2015) and Menon and Rodgers (2017) for reviews of work on developing countries. Clemens (2021) provides an analytical framework to understand how firms may adjust non-wage compensation and hours to dampen the effect of the minimum wage. This may help explain small aggregate disemployment effects in the U.S. In support of this idea, Clemens et al. (2018) find a decline in employer-provided health insurance provisions, while Yu et al. (2021a,b) find a decrease in hours per worker associated

ments of change to firms' input mix and production structure has received little attention.[4]

I fill this gap by building on the automation and offshoring literature to study how different firms adjust their capital investment and labor inputs following minimum wage increases in their respective industries and states. I use granular Indian firm-level data on machinery and computer investment, as well as employment data for workers and managers, and exploit frequent variation in local industry minimum wages to explore the following questions: (1) How do individual firms invest in different types of capital, and adjust their employment of workers and managers as the relative cost of frontline labor to capital increases? (2) How does this adjustment differ for firms in industries more intensive in routine and offshorable tasks?[5]

Using an array of Indian datasets and concordance tables between India and the U.S., I bring common measures of routineness and offshorability used in the literature to the Indian economy. In particular, I use the Routineness Intensity measure (RTI) introduced by Autor and Dorn (2013) and Autor et al. (2013) and the measure of offshorability proposed by Firpo et al. (2011) and

with a decrease in benefit eligibility, following minimum wage hikes in the U.S.

[4] A small body of research has investigated the role of minimum wages on productivity and profits. For example, Draca et al. (2011) and Bell and Machin (2018) find that minimum wage hikes in the UK lower firms' profits and the market value of low-wage firms, respectively. Ku (2020) and Hill (2018) find a conflicting effect on worker-level productivity, while Coviello et al. (2021) find that the effect on worker-level productivity depends on monitoring intensity.

[5] Routine tasks are usually repetitive, and are successfully accomplished by following a clear and known set of rules (Autor et al. (2003)). When this is the case, it is easier to design a machine or computer code to perform the task. Suppose that a task involves repetitively moving homogeneous pieces off of an assembly line and onto a conveyor belt. It is easy to design a machine to do this task since the pieces to be picked are homogeneous; they reach the end the assembly line at known intervals, and it is possible to define a clear set of motions that correctly move the pieces from point A to point B. Managers may be tasked with motivating workers to ensure that they remain productive. While this may be a repetitive task with a clear goal, there is no clear or unique way to perform this task. Thus, it is much harder to automate.

Acemoglu and Autor (2011).[6] As a source of input cost shifter, I construct a comprehensive database of all formal industry-level minimum wages in the country from 2002 to 2008. India is particular in that the minimum wage changes at the state, year, and *industry* level, with the average industry experiencing a nominal increase in its minimum wage every year and a half.[7] This provides a wealth of plausibly exogenous variation in the cost of frontline employees. Moreover, the granularity of the variation allows me to control for industry- and district-specific shocks without soaking up much of the identifying variation.[8] By doing so, I account for other confounding policies and factors such as aggregate changes in labor or output demand, and changes in the cost of capital goods. The wealth of variation in the minimum wages, the fact that the minimum wage in an industry is binding for most firms in that industry (ILO (2018)), and that firms had not fully automated or offshored their production in the early 2000s (Mani (2019)), make India over this time period an ideal context to study how firms adjust to changes in relative input prices.[9] To quantify the effect of changes in the relative cost of labor inputs,

[6] A task is more offshorable if it is possible to do at least part of the task remotely while supplying the task's output at the place of production, at little or no cost. This measure captures the degree to which face-to-face interactions, and on-site presence, are necessary. For example, a firm producing bolts must ensure that the diameter of the bolts remain within a particular range. If too many bolts fall outside this range, the machines may need to be adjusted. One can imagine that analysts charged with determining whether too many bolts are faulty, can do their analysis remotely relatively easily. However, the workers placing the boxes of bolts onto a truck for shipping must be physically present to complete their task, making it harder to offshore.

[7] While not all industries have a statutory minimum wage, 40% of the entire non-agricultural workforce (100 million people) are entitled to receive minimum wages (India Briefing (2020), Majumdar (2008)). Using data from the National Sample Survey presented in the data section, I estimate that in 2008, 61 million people are working for wages in industries with a minimum wage and 42.1 million of them are paid $\leq$ 120% of the minimum wage in their industry. I.e., the minimum wage is likely to affect up to 42.1% of the workforce in formal firms or 17% of the entire non-agricultural workforce. Estimates from Cengiz et al. suggest that around 10% of the U.S. workforce is paid the statutory minimum wage prevailing in their respective state (15.7 million people in 2008).

[8] I include district-by-year and industry-by-year fixed effects in the regressions. Indian states are divided into districts. Districts are akin to counties in the U.S. Territories are not included in the analysis.

[9] India was not facing a recession during the study period.

I adopt a difference-in-difference approach and compare the adjustment in investment and employment of firms experiencing a minimum wage increase to that of firms that do not experience a hike, before and after the minimum wage increase.

I propose a task-based production model in order to get predictions on how firms adjust their inputs following changes in the cost of these inputs (in the spirit of Acemoglu and Zilibotti (2001), Acemoglu and Autor (2011), Goos et al. (2014), Acemoglu and Restrepo (2018)). In addition to capital, I include four types of frontline employees: regular workers, contractual workers, managers, and offshore workers.[10] In the model, firms combine tasks to produce an output, and tasks are produced by combining inputs using CES production functions. The elasticity of substitution between inputs within tasks depends on how routine and offshorable the tasks are. The model predicts the status quo or an increase in the demand for capital in India for firms intensive in neither routine nor offshorable tasks, and a clear increase in capital in routine-intensive firms following a minimum wage hike. The model predicts an increase in offshore labor and capital for firms intensive in offshorable tasks, and a fall in the demand in India for the group of workers affected the most by the minimum wage in all types of firms. These predictions are largely consistent with the results of the empirical analysis.

I find that firms invest in computers and machinery at the rates of 7.8% and 8.3% per year on average, respectively. Firms in the average industry, that is, firms in industries intensive in neither routine nor offshorable tasks, do not meaningfully change their investment patterns following a typical (real)

[10]Regular or payroll workers are hired directly by the firm, appear on the muster roll, and receive employment benefits. Contractual workers also work in the same firms, but are hired externally, generally through contracting intermediaries. Most contract workers are lower skilled and less educated workers from socially disadvantaged groups. They are usually paid only for their days worked, and often work irregular schedules (ILO (2018)).

minimum wage hike (approximately 2.5 rupees).[11] On the other hand, firms in routine-intensive industries boost their rate of investment in computers and machinery.[12] Firms in industries one standard deviation (SD) above the mean in terms of routineness intensity invest, on average, 6.1% more in machinery and 4% more in computers following a typical minimum wage increase. Firms in industries more intensive in offshorable tasks also continue to invest in machinery and computers, but the rate of investment in computers falls by 6.2%. When the minimum wage binds for regular workers, the number of regular workers working during a typical workday falls by 0.44-1.2 workers (0.5%-1.36%). Firms in the average industry and firms in more offshorable industries substitute some of these workers with contract workers and managers less likely to be bound by the minimum wage. Given that the latter group of firms also experiences a fall in computer investment following a minimum wage hike suggests that some tasks that combine workers and computers, like data analysis, may be offshored.[13] There is less evidence of substitution across labor inputs in routine-intensive industries, indicating that most of the substitution takes place between regular workers and capital. The adjustments made by firms allow them to maintain their profit margins without changing their level of production.

The empirical strategy I use in this study exploits variation from all firms. An alternative is to focus on firms in districts along state borders only, since

[11] Firms in the average industry are firms in industries with average routineness and offshorability intensity. The routineness and offshorability measures are normalized to be mean 0 and standard deviation 1 in 2000, across all industries. I refer to firms in routine-intensive industries when the routineness index is at least1 SD above the mean, and refer to firms in industries intensive in offshorable tasks when the offshorability index is at least 1 SD above the mean.

[12] Unless otherwise stated, all changes in wages are in real 2008 rupees.

[13] I do not have data on their employment of offshore labor, but I find no evidence of an increase in outsourcing for these firms. This suggests that offshoring is the more likely channel.

they may evolve in more similar environments (Card and Krueger (2000), Dube et al. (2010)). This concern is partially accounted for by including district-by-year fixed effects in the main specifications. Nevertheless, I show that the results are similar when using this contiguous design. The results are also robust to using only variation from real minimum wage increases that exceed inflation. They are also robust to controlling for the average minimum wage in other industries of the same state, capturing the potential changes in the outside option of people employed in a given industry.

This study contributes to the literature establishing a link between relative input costs and automation and offshoring trends. Many authors have theorized that routine tasks and tasks that can be done remotely are more likely to be, respectively, automatized and offshored as the relative cost of labor inputs increases. These predictions are consistent with the results of this essay (in addition to the authors mentioned previously, see Autor et al. (2003, 2006), Antràs et al. (2006), Blinder et al. (2009), Goos and Manning (2007), Goos et al. (2009), Blinder and Krueger (2013), Brynjolfsson and McAfee (2014, 2017), Autor et al. (2015)).[14] Most research in this literature uses aggregate employment data to document trends consistent with this theory by leveraging different sources of variation such as the falling cost of technology (Beaudry et al. (2010), Autor and Dorn (2013), Goos et al. (2014)), or the rise in the cost of labor through changes in the U.S. state-level minimum wage. In particular, Aaronson and Phelan (2019) as well as Lordan and Neumark (2018) have investigates the heterogeneous effects of increases in state minimum wages in the U.S. depending on the routineness and offshorability of different occupations. Using population survey data, Aaronson and Phelan find that an increase in

[14] An analogous literature explores variation in exposure to technology (Michaels et al. (2014), Graetz and Michaels (2018), Bessen et al. (2019), Acemoglu et al. (2020), Acemoglu and Restrepo (2020)).

the cost of labor in low-wage employment leads to a decrease in aggregate employment for people employed in routine occupations. Using the same data, Lordan and Neumark find that increases in the minimum wage lead to a fall in employment for low-skilled workers in routine-intensive occupations. Here, the objective is to better understand how firms adjust their inputs when they differ in their capabilities to offshore or automate tasks. However, in exploratory analyses, I find evidence that minimum wage hikes reduce employment at the national level for younger workers across all types of industries and for older workers in routine-intensive industries.

Little work has explored how rising minimum wages affect capital investment at the firm-level. A notable exception is Hau et al. (2020) who consider whether hikes in the county-level minimum wages in China affect manufacturing firms' input choices.[15] The authors investigate whether minimum wage hikes affect firms responses differently whether they are state-owned, privately owned by nationals, or privately owned by foreign parties. They find that an increase in the minimum wage leads to a shift from workers to capital especially in foreign-owned private firms. This pattern is less pronounced in Chinese-owned private firms and in state-owned firms. Suggestive evidence indicates that these three types of firms differ in managerial quality. Hence, the authors suggest that differences in management structures may drive the heterogeneous responses following the minimum wage hikes observed across the three firm types. Here, I propose another explanation, and provide evidence that the differences in responses across firms may, instead, be driven by differences in their capability to offshore and automate certain tasks.

In additional analyses, I investigate the role of layoff regulations, and find

[15] See also Haepp and Lin (2017) who study the same context and find a decrease in training expenditure per worker which they take as a measure of investment in human capital, and find no change in physical capital investment.

that the firm-level responses to minimum wage hikes differ depending on how easy it is to layoff workers in their state. Therefore, I contribute to the literature on the effect of different layoff regulations on firms (see for example Besley and Burgess (2004), Aghion et al. (2008), Adhvaryu et al. (2013) Adhvaryu et al. (2013) andAmirapu and Gechter (2020) for a recent review). Building on Aghion et al. (2008), I identify pro-employer, pro-worker, and neutral states that have, respectively, facilitated, hindered, or left unchanged, the difficulty of laying off frontline workers over the years. I find that adjustments in capital and labor inputs are greater in pro-employer states. This indicates that other labor regulations play a key role in determining how firms adjust to changes in the costs of their inputs.

The remainder of this essay is organized as follows. In Section 2, I describe how minimum wages are set in the formal economy. I also present the datasets used, and provide summary statistics. The model and its predictions are introduced in Section 3. Section 4 presents the empirical strategies I employ, followed by the results in Section 5. Finally, I conclude the essay in Section 6.

2 Data and summary statistics

Table 1 lists the different datasets used and provides summary statistics for the key variables used in the essay.

Table 1: Datasets and summary statistics

Data Sets & Brief Description	Years Included and Level of Observations	Key Variables	Key Statistics of the Study Sample
Report on the Working of the Minimum Wages Act- Universe of formal minimum wages in India	Years: 2002-2008 inclusive. All minimum wages at the state, industry, and year level	-Indian minimum wages for the formal economy	-Nb of 4-digit industry min. wages: 6,325 -Nb of nominal changes: 2,587 -Avg percent of industries with min. wage across state: 45% (SD 20) -Avg nb years until change: 1.5 (SD .6) -Avg nominal min wage: ₹ 80.5 (SD 21) -Avg real min wage: ₹ 94.5 (SD 23)[a] -Avg real min wage change: ₹ 2.5 (SD 8)
Prowess- Yearly income statements of the universe of publicly listed firms in India	Years: 2002-2008 inclusive. Balanced panel of public firms	-Investment in: -Capital -Machinery -Computers -Profit margin	-Number of firms: 18,438 [b] -Avg capital investment: 12.3% (SD 68)[c] -Avg machinery investment: 7.8% (SD 49) -Avg computer investment: 8.3% (SD 66) -Avg profit margin: 2.1% (SD 19)[d]
Annual Survey of Industries (ASI)- Representative survey of formal manufacturing firms in India	Years: 2002-2008 inclusive. Unbalanced panel of manufacturing firms	-Number of each type of employees working in an 8-hour shift -Number of mandays paid for each type of employees over the year -Total wage and non-wage compensation per day for the average employee -Type of employees: -Regular Workers -Contract Workers -Managers	-Number of firms: 44,759 Avg number of employees per 8h shift: -Regular workers: 88 (SD 111)[e] -Growth nb employees: .9 (SD 40) [f] -Contract workers: 53 (SD 57) -Growth nb employees: 2 (SD 39) -Managers: 13 (SD 17) -Growth nb employees: .3 (SD 7) Avg yearly number of mandays paid to: -Regular workers: 25,885 (SD 33,741)[e] -Growth nb mandays: 393 (SD 12,439)[f] -Contract workers: 15,490 (SD 17,296) -Growth nb mandays: 708 (SD 11,725) -Managers: 3,719 (SD 5,116) -Growth nb mandays: 108 (SD 2,128)
O*Net- task content of U.S. occupations	Year: 2000. Occupation level	-Routineness; and -Offshorability of U.S. occupations	Provides raw routineness (Autor and Dorn, 2013) and offshorability measures (Firpo et al., 2011) for 500, 4-digit US occupational codes
National Sample Survey (NSS)- Representative survey of Indian households	Year: 2000. Repeated cross-section of households	-Main occupation -Industry of main occupation	Used to construct measures of routineness and offshorability for the different Indian industries from crosswalks between U.S. and India occupational codes. The measures are mean 0 and SD 1 in 2000 across Indian industries.

Note: a- The real minimum wage is in rupees of 2008. b- Only firms with nonzero net value of capital for some years over the sample are included. c- The investment variables are winsorized at the top 2.5% and bottom 1%. Capital is the combination of machinery and computers. The mean capital investment is larger than the mean of its individual components because a firm can invest in machinery, but not in computer or vice versa for certain years. d- the profit margin can be negative as firms can make losses and large outliers exist most likely because the net revenue (revenue after expenses) can be close to 0. Hence, I winsorize the top and bottom 7.5% of values for this variable. e-The employment averages are conditional on having a positive number of the type of employee listed at any point during the study period. The variables are bounded at 0 so I wisorize the top 5% of values. f- The growth statistics represent the average yearly within-firm growth in the number of employee, mandays, and compensation for the different type of employee conditional on having a positive number of employee of this type at any point during the study period.

2.1 Minimum wages in the formal economy

Context

In the Minimum Wage Act of 1948, the federal government of India mandated that states establish minimum wages in a group of predetermined industries in the formal economy.[16] Although the initial group is common across the country, individual states have added different industries to this list since 1948. The Act states that the minimum wages listed apply to any employee working in these industries, regardless of their age, gender, or work arrangements, unless explicitly mentioned (Soundararajan (2019)).[17]

The Act recommends that states designate committees consisting of both employers and employees, as well as state officials, to make recommendations with regards to wage fixation and revision. However, the state governments ultimately determine the prevailing wages. The Act does not dictate which methodology states should follow in revising their wages, rendering the decision process opaque and the wage hikes hard to predict (Soundararajan (2019), Adhvaryu et al. (2021c)). However, the Act stipulates that revised wages be posted in the states' official gazettes at most three months before they come into effect on the first of January of the coming year. Firms are required to pay the set wages, and compliance is verified through inspections by designated

[16] The industries in the original group are often referred to as the scheduled employments under the Minimum Wage Act (see Appendix A). Scheduled employments refers to those listed in the schedule appended to the Minimum Wages Act, or any process or branch of work constituting part of such employment (Minimum Wage Act (1948)). While they use the term "employment", it refers to industries (4-digit) and sometimes, subindustries (5-digit) rather than occupations or jobs. For example, we can find in the original list a minimum wage for individuals employed "in any tobacco (including bidi making) manufactory" or individuals employed in "in any rice mill, our mill, or dal mill."

[17] This includes regular workers, contract workers, and managers. However, as I mention in Subsection 2.3, enforcement of the minimum wages may not be as strong for contract workers as for other employees.

officials.[18] Moreover, states must revise the minimum wages at least every five years, and as I show below, nominal wages are increased every year and a half, on average.[19]

In 2005, India passed The National Rural Employment Guarantee Act (NREGA) which may confound the analysis in this study. This Act stipulates that rural households be guaranteed 100 days of public work at a minimum wage set by the respective states. The program was rolled out sequentially during the last few years of the study period (2006-2008). The most common work provided is short-term unskilled manual work.[20] However, NREGA does not cover formal firms in the private sector. Nevertheless, the program can drain workers away from the private sector and put upward pressure on low-skill manual workers' wages. As I explain in the empirical strategy section, the data I use is very granular. Therefore, I can account for the NREGA roll-out by controlling for district-specific shocks.

Data

I construct a comprehensive list of industry minimum wages for firms in the formal economy across India from 2002 to 2008. To do so, I digitized

[18] In addition, workers can submit claims to Labor Commissioners whenever their employer pays less than the statutory wage in their industry.

[19] In 1991, the National Commission on Rural Labour recommended the implementation of a National Floor Level Minimum Wage (NFLMW) in response to variation in minimum wages across states. In 1996, this wage was introduced as a recommendation for the different states, rather than as a binding minimum wage, and it was left to the discretion of the states whether to follow the recommendation. The Indian government is now thinking of implementing a binding national minimum wage. Hence, the results of this research may prove valuable for Indian policy makers.

[20] Imbert and Papp (2015) have studied the program and determined that the average recipient is able to claim 38 days of guaranteed work, and the median household is only able to claim about a month of guaranteed public work across all members of the household. Moreover, they find that recipients are usually earning less than the state-set NREGA wage because there are large discrepancies across states as to whether they respect the guidelines set by the federal government. See also Sharma (2009), and Dreze and Khera (2009).

all formal minimum wages from annual federal government reports.[21] All minimum wages are in the form of a minimum wage per eight-hour workday.[22]

Then, I map the wages for the listed industries to their equivalents in the National Industry Code (NIC) in order to merge the minimum wages with firm-level datasets. In the vast majority of cases, the minimum wages listed correspond to 4-digit industries, which makes the mapping simple. However, in some cases, minimum wages correspond to 5-digit sub-industry codes. From the NIC, I can distinguish how many 5-digit sub-industries there are within any 4-digit industry. Therefore, I average the minimum wages within 4-digit industries in these cases.[23] Since there is no national wage floor, I assume that the minimum wage is 0 in industries and sub-industries that do not appear in the minimum wage reports like Menon and Rodgers (2017, 2018).

From the exercise above, I find over 6,300 industry-year observations with a set minimum wage, as summarized in Table 1. States have a set minimum wage for 45% of their 4-digit industries on average (ranging from 7-82% across states). Over the span of the data, I observe 2,600 nominal wage increases occurring every year and a half, on average. Among industries with a minimum wage, the average nominal minimum wage is approximately 80.5 rupees per workday (ranging from 28-163 rupees across industries and states). However, throughout the analysis, I use the minimum wage in constant rupees of 2008 by deflating the minimum wages by the consumer price index for that year.[24] I find that the real daily minimum wage is approximately 94.5 rupees (ranging

[21] The reports are titled "Report on the Working of the Minimum Wages Act, 1948 for the year t", with t being the year of the report, e.g., $t = 2001$. Each year, approximately 700-1,000 minimum wages are listed across all states and industries.

[22] Listed minimum wages in older reports often vary format across states, and even across reports for the same state.

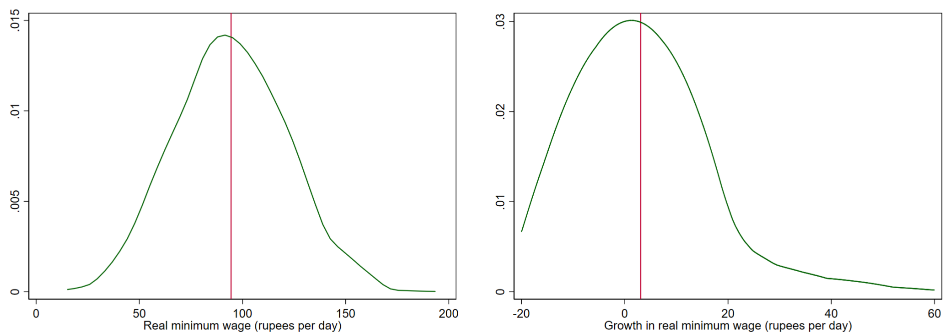
[23] There are 102 four-digit industries in the NIC classification.

[24] I use the same deflator across all states in a given year. Although some states produce their own CPI, they are not harmonized across states, and not all states construct this metric (MOSPI (2021)).

from 30-179 rupees). When the nominal minimum wage increases, it does so by 8 rupees on average, or 2.5 rupees in real terms. This corresponds to a 9.9% and 3.1% increase, respectively.[25] Figure 1 shows that there is extensive variation in the distribution of real minimum wages, and in the distribution of annual growth rates in the real minimum wages across industries and states in Panels (a) and (b), respectively.

Figure 1: Distribution of the average real industry minimum wages and their grow rates across industries and states

(a) Real minimum wage (b) Average yearly growth rate



Note: I compute the average real minimum wage across years for every industry and state, and plot the distribution across industries and states in Panel (a). I compute the average real minimum wage growth across years for every industry and state, and plot the distribution across industries and states in Panel (b). The vertical line represents the average: 94.5 rupees per day in Panel (a), and 3.1% in Panel (b). I trim the figure in Panel (b) at -20% and 60%. These bounds are smaller, and larger, than the first and 99th percentiles, respectively.

In Appendix C, I compile three waves of India's nationally representative household survey data that span over my study period. This data contains information on working individuals' wages and the industry in which they are employed. I regress the real daily wage of working individuals on the

[25]In terms of PPP, this represents an increase of $0.10 per hour in 2020 dollars every year and a half. Comparatively, U.S. states saw an increase in their nominal minimum wage every 3 years between 1990 and 2005, with an average increase of approximately $0.50 in real terms. I computed the U.S. statistics using replication data from Dube et al. (2010).

real minimum wage.[26] I find that every rupee increase in the real minimum wage of an industry is associated with a 0.28 rupees (SE 0.12) increase in the average real wage for people employed in that industry. This indicates that the minimum wage binds for a large percentage of workers.

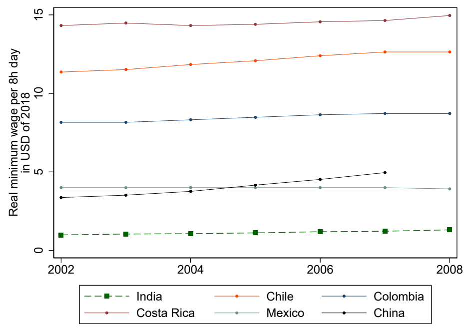
For perspective on Indian minimum wages, and the pace at which they grow, I compare them to minimum wages in other developing countries. The OECD tallies minimum wage data for a subset of countries including a handful of South-American developing countries in real 2018 dollars.[27] I compute the average real minimum wage in dollars across all states and industries with a set minimum wage for every year. In Figure 2, I compare the average Indian minimum wage to the national minimum wages of Chile, Colombia, Costa Rica, and Mexico in real dollars per 8-hour workday. I add China's minimum wage to the list using numbers reported by Haepp and Lin (2017). As shown in the first panel, the Indian wage is lower than that of any other country on the list, ranging from $1 per day in 2002 to $1.30 per day in 2008, in real terms. However, India's average minimum wage grows faster than any other country listed, except for China.

[26] The firm-level datasets used in the main analysis do not contain wage data.

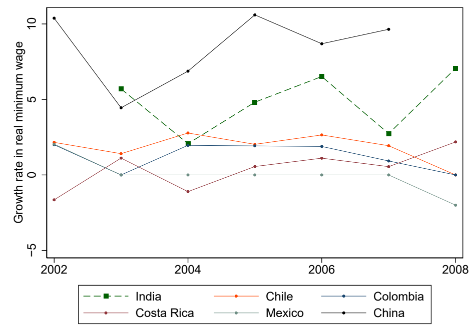
[27] The data can be found at: https://stats.oecd.org/Index.aspx?DataSetCode=RMW

Figure 2: Real minimum wage in U.S. dollars of 2018 and its growth rate across as sample of developing countries

(a) Real minimum wage



(b) Growth rate



Note: I convert the Indian minimum wages into 2018 USD per hour. I average the real minimum wages across states and industries for every year for industries and states with a statutory minimum wage. I plot the average real minimum wages in Panel (a) and the yearly growth rates in Panel (b).

2.2 Investment data

The Prowess dataset is a balanced panel of the quasiuniverse of publicly listed firms in India. The data is at the firm level, and is constructed from firms' annual and quarterly financial statement filings. This dataset is ideal for studying investment decisions of firms since they have to list the value of their capital inputs, the industry they are in, and their location, as part of their filings.[28]

I define the net value of capital as the sum of the net value of machinery and the net value of computers, software, and related IT equipment.[29] Machinery

[28] I assume that firms primarily produce in their districts of incorporation. The dataset also includes the district of firms' corporate offices and head offices. However, 90% of the firms have all offices in the same district.

[29] I add software expenditure to the computer category, as the two are intrinsically linked and it is unclear from the data whether all firms separate the two.

includes all forms of physical capital needed in the firm's productions other than computers, software, and IT equipment. This category includes hydraulic and electric tools, machines, conveyor belts, etc. (see appendix B for details on the variables.) Then, I follow Yagan (2015) and construct a measure of aggregate capital investment by computing the change in net value of capital, as follows.[30]

$$I_{ft} = 100 * \frac{\text{Net Value of Capital}_t - \text{Net Value of Capital}_{t-1}}{0.5(\text{Net Value of Capital}_{t-1} + \text{Net Value of Capital}_{t-2})}.$$

In the equation above, the numerator corresponds to the difference in the value of capital at the end of the year t, and at the beginning of the year $t-1$, net of depreciation. The denominator captures the net value over the previous year. It is constructed by averaging between the end-of-year and beginning-of-year net capital value of the previous year.[31] Therefore, I_{ft} captures the percentage change in physical capital over the course of year t for firm f.

I also separately compute the same measures of investment for machinery and computers.[32] I find that firms invest, on average, at a yearly rate of 12.3% in capital, 7.8% in machinery, and 8.3% in computers, as presented in Table 1.

[30] I winsorize the top 2.5%, where outliers are more likely, and bottom 1% of values. When firms have no capital and invest for the first time, then the value investment is infinity for the first investment year. Winsorizing ensures that these cases do not drive the results. I show that the main results are robust to winsorizing the top and bottom 1% of values in Appendix E.

[31] This normalization is common in the corporate finance literature. See also Luck and Zimmermann (2020).

[32] Given this definition, firms are included in the analysis only if the net value capital, as defined above, does not equal 0 for some years in the data. Firms without any capital over the study period are excluded. If a firm has some machinery (i.e., the net value of machinery is positive), but no computers for two consecutive years, then I assume that investment in computers is 0 in the second year, and vice versa for machinery, if a firm has computers, but no machinery for two consecutive years.

Since the data has a balanced-panel structure, I include firm fixed effects in the regressions below to account for firms' time-invariant characteristics. However, I also include time-varying controls that are often used in the corporate finance literature. In particular, I include fourth-degree polynomials in the age of the firms, lagged revenue, lagged profit margin, and lagged revenue growth (Yagan (2015)).[33]

2.3 Employment Data

While the balance sheet data from Prowess is very detailed, it suffers from one major flaw: firms do not have to report how many employees they have.[34] Therefore, I rely on India's Annual Survey of Industries (ASI) for employment information. The ASI is a survey of registered (formal) firms from over 40 four-digit manufacturing industries which represents a coverage of about 40% of all 4-digit industry categories. The data includes all establishments with 10 or more employees if they use electrical power, and 20 or more employees if not. Firms are surveyed at least every 5 years using an efficient sampling design (Indira et al. (2010), Chaurey (2015)). Employment is divided into three main categories: regular (payroll) workers, contract workers, and managerial staff involved in the production process. Regular or payroll workers are employed directly by the firm; they appear on the firm's muster roll, and their wages must be greater than or equal to the minimum wage, if there is one in their industry, and they receive job-security benefits. Non-permanent contract workers also work at the firm, but they are employed on short-term contracts

[33] For the controls, "lagged" indicates the average between the end-of-year and beginning-of-year variable values during the previous year.

[34] In fact, only an insignificant amount of firms does report it.

through an intermediary such as a labor contractor or an agent. These workers usually receive no benefits, as they are employed through intermediaries. While enforcement is strict with respect to the minimum wage paid to regular workers, it is not as strict for non-permanent workers. As a result, contract workers are generally paid less than regular workers due to lack of enforcement for this subgroup, and because they are often employed through oral agreements (see Srivastava (2016) for a review). In the context of this study, this means that changes to the formal minimum wages likely have a lesser effect on contract workers' wages than on those of regular workers.

In the ASI, firms report how many mandays each type of employee worked (regular workers, contract workers, and managers). This variable represents the total number of full days worked across every employee of a particular type during the year.[35] Firms also report the average number of employees working on a typical workday during the reported year for every employee group.[36]

Firms in the sample employ, on average, 88 regular workers, 53 contract workers, and 13 managers in a typical eight-hour day, as summarized in Table 1. As a result, firms report 26,000 full workdays paid to regular workers, 15,500 to contract workers, and 3,700 to managers.[37] Taking the ratio of the two variables indicates that regular workers and contract workers typically work 294 full days per year, or 24-25 days per month. Managers work on average 284 full days during the year, or 23-24 days per month. This means a typical employee works full-time given that in India, a full workday is eight

[35]For example, I find that firms report 26,000 full workdays paid to regular workers on average. A full workday is eight hours. This means that if we were to sum the number of 8-hour workdays across all regular workers, we would arrive at 26,000 workdays for this group.

[36]I winsorize the top 5% of values. The minimum values are bounded by 0. Therefore, there is no need to winsorize the bottom of the distribution. The results are also robust to winsorizing the top 1% of values (see Appendix E).

[37]The averages are conditional on employing a positive number of the type of employee mentioned.

hours and that a usual workweek is six days.[38]

2.4 Routineness and Offshorability of Industries

I map the measures of routineness and offshorability used by Acemoglu and Autor (2011) to Indian industries.[39] Doing so allows me to assess whether increases in minimum wages have heterogeneous effects across industries.[40]

The authors use the task composition of occupations to measure occupational routineness and offshorability.[41] The task composition of occupations

[38] Note that firms do not report the total number of employees they have paid in the year, but this total would not capture adjustments done during the year or changes in the intensity of work. On the other hand, the number of mandays and the average number of employees working does account for these adjustments and changes.

[39] These measures have been generously made available by Prof. David Autor and can be found on his website. The RTI measure used Acemoglu and Autor (2011) is based on the original work of Autor et al. (2003). The two papers follow the same methodology, but the former relies on task-content of occupations as of 1998, while the latter uses the mapping of 1991. The offshorability measure builds on the work of Firpo et al. (2011), but excludes scales that may overlap with the routineness measure. See Acemoglu and Autor (2011)'s data appendix for a precise exposition how they map task content to the routineness and offshorability measures.

[40] Routine tasks are usually repetitive, and are successfully accomplished by following a clear and known set of rules (Autor et al. (2003)). When this is the case, it is easier to design a machine or computer code to perform the task. Suppose that a task involves repetitively moving homogeneous pieces off of an assembly line and onto a conveyor belt. It is easy to design a machine to do this task since the pieces to be picked are homogeneous; they reach the end the assembly line at known intervals, and it is possible to define a clear set of motions that correctly move the pieces from point A to point B. Managers may be tasked with motivating workers to ensure that they remain productive. While this may be a repetitive task with a clear goal, there is no clear or unique way to perform this task. Thus, it is much harder to automate.

[41] A task is more offshorable if it is possible to do at least part of the task remotely while supplying the task's output at the place of production, at little or no cost. This measure captures the degree to which face-to-face interactions, and on-site presence, are necessary. For example, a firm producing bolts must ensure that the diameter of the bolts remain within a particular range. If too many bolts fall outside this range, the machines may need to be adjusted. One can imagine that analysts charged with determining whether too many bolts are faulty, can do their analysis remotely relatively easily. However, the workers placing the boxes of bolts onto a truck for shipping must be physically present to complete their task, making it harder to offshore.

comes from the Occupational Information Network database (O*NET) of the U.S. Department of Labor. Therefore, the routineness and offshorability measures these authors propose are at the U.S. occupation level which follows the Standard Occupation Classification (SOC). India has its own National Classification of Occupations (NCO). Fortunately, both national classification systems have been harmonized in recent decades to be compatible with the International Standard Classification of Occupations (ISCO). Hence, it is possible to map the routineness and offshorability measures to India's occupations.[42] However, the firm-level data sets presented above are at the industry, rather than the occupation level. Below, I explain how I aggregate the measures at the industry level.

Before doing so, I provide anecdotal evidence that the task content of occupations in India is similar to that of the U.S. While the ideal approach would be to construct the routineness and offshorability measures from task-to-occupation mappings in India, such mapping has only been done in the U.S., as far as I am aware. However, in 2015, the Department of Labor of India launched the National Career Services website. This platform was created to provide career information and to connect employers with job seekers. Job seekers interested in determining whether their skillset matches certain occupations are referred to the O*NET interest profiler (see Bhatnagar (2018)). This suggests that the Indian government considers the skill requirements of occupations characterized in O*NET to be a good proxy for occupations in India.[43] If the skill requirements are similar, then it is unlikely that occupations

[42] Goos et al. (2014) follow a similar strategy for Western European countries.

[43] Blinder and Krueger (2013) provide alternative metrics of offshorability. However, their measures come from a snapshot of the US economy at the end of my study period. Moreover, they do not rely on O*NET's task composition of occupations. Hence, the measures may not be applicable to the Indian context during the study period. They recruited professional coders to subjectively rate the offshorability of occupations from a 2008 survey of 2,500 U.S. labor force participants.

are too dissimilar in terms of tasks.

Firms in Prowess and the ASI are classified using the National Industry Classification (NIC). Of course, occupations do not align one-to-one with the industry classifications. For example, cashiers can be found in multiple industries. Fortunately, India's main household survey, the National Sample Survey (NSS), records the 3-digit NCO occupation of employed people in the sample, and the 5-digit industry in which they work.[44] I average the measures from the authors above at the 4-digit industry level using the NSS sampling weights for the 2000 survey wave.[45] The measures are normalized to have a mean of 0 and a standard deviation of 1 across all 4-digit industries in 2000. This strategy allows me to construct measures capturing how routine and offshorable the tasks and occupations are in every Indian industry, just before the study period. The measures can then be merged with the firm-level datasets used in the essay.[46]

Among the most routine occupations in India, I find office and numerical clerks, cashiers, bank tellers, food processing workers, and textile machine operators. Pasta manufacturing, the production and preserving of meat products, bakery products manufacturing, and man-made fiber manufacturing are among the most routine industries. Among the most offshorable occupations, I find social science professionals, mathematicians and statisticians, numerical clerks, and computing professionals. Man-made fiber manufacturing, game and toy manufacturing, software development, and call centers are among the

[44] The National Sample Survey (NSS) is a nationally representative cross-sectional survey of households.

[45] The survey is conducted at irregular intervals, and employment questions are not asked in all waves. The 2000 wave is the only usable wave that took place before the study period. The previous survey wave with employment data was conducted in 1993, before the country opened its economy.

[46] I calculated both the unweighted average and the weighted average using sampling weights. There is a strong correlation between unweighted measures and weighted measures ($\rho = 0.8$). Therefore, I use the weighted mean in the main analysis.

industries with the most offshorable occupations. As we can see, the routineness and offshorability are not mutually exclusive.[47] Hence, it is important to analyze them in tandem.

3 Model

In this section, I construct a simple task-based production model in the spirit of Acemoglu and Restrepo (2018) in order to derive predictions on the firms' adjustments. In the model, firms produce a single output, Y, by combining a continuum of tasks, $y(i)$ with $i \in (0,1)$, through a CES production function:

$$Y = (\int_0^1 y(i)^{\frac{\sigma-1}{\sigma}} di)^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

where $\sigma \in [0, \infty)$ is the elasticity of substitution between the tasks. Without loss of generality, I assume that the technology component equals 1. Next, I assume that tasks can potentially be done by different inputs, namely contract workers (c), regular workers (l), managers (m), and capital (k). Offshore inputs are discussed in the discussion section below. I assume that the production function for tasks also has a CES structure, as presented in Equation (2) below.

$$y(i) = (\sum_{j \in \{c,l,m,k\}} [\delta_j(i)]^{\frac{\varepsilon_i - 1}{\varepsilon_i}} \times [j(i)]^{\frac{\varepsilon_i - 1}{\varepsilon_i}})^{\frac{\varepsilon_i}{\varepsilon_i - 1}}, \text{ or} \tag{2}$$

[47] In fact, at the industry level, the correlation between routineness and offshorability is 0.67.

$$y(i) = (\sum_{j \in \{c,l,m,k\}} \gamma_j(i) \times j(i)^{\rho_i})^{\frac{1}{\rho_i}}. \tag{3}$$

In Equation (2), $\delta_j(i)$ is the productivity of input j at task i. The element $j(i)$ is the number of input j used in task i, and $\varepsilon_i \in [0, \infty)$ is the elasticity of substitution between inputs for that task. While certain tasks may use all inputs listed above, other tasks may use only regular workers and capital, for example. In such a case, only $\delta_l(i)$ and $\delta_k(i)$ would be different from 0, and positive. To ease the notation, I replace $[\delta_j(i)]^{\frac{\varepsilon_i - 1}{\varepsilon_i}}$ with $\gamma_j(i)$ and $\frac{\varepsilon_i - 1}{\varepsilon_i}$ with ρ_i to obtain Equation (3).

I chose this general class of functions for the task production since it imposes few restrictions on which inputs are used in a particular task. This can accommodate cases where a given input is used differently across tasks. For example, computers may be used as substitutes for some workers in quality-control tasks, while computers may complement managers in monitoring tasks.

In order to have a tractable solution, I assume that all inputs of the same type have the same wage, and that firms take wages as given, and follow a typical two-step cost minimization as in Acemoglu and Restrepo (2018) and Goos et al. (2014). In the first step, firms minimize each task's production costs by choosing inputs. In the second step, they minimize the final output's production costs by choosing how many iterations of each task is done. The ratio of the FOCs for the cost minimization of task i for any two inputs, j and j', can be expressed as:

$$\frac{w_j}{w_{j'}} = \frac{\gamma_j(i)}{\gamma_{j'}(i)} (\frac{j(i)}{j'(i)})^{\rho_i - 1},$$

where w_j and $w_{j'}$ are the wages of these inputs to the firm after any adjustments. By plugging the last equation in (3) and solving for $j(i)$, we obtain the factor demand for input j in task i conditional on $y(i)$.

$$j(i) = y(i)(\frac{\gamma_j(i)}{w_j})^{\frac{1}{1+\rho_i}}(\sum_{j\in\{c,l,m,o,k\}}(\gamma_j(i))^{\frac{-1}{\rho_i-1}}w_j^{\frac{\rho_i}{\rho_i-1}})^{\frac{-1}{\rho_i}} \tag{4}$$

Similarly, the task demand conditional on output from the cost minimization of tasks can be written as:

$$y(i) = Yp(i)^{-\sigma}, \tag{5}$$

where $p(i)$ is the unit cost of task i which is defined as $p(i) = \frac{1}{y(i)}(\sum_{j\in\{c,l,m,k\}} w_j j(i))$. Then, plugging Equation (4) in $p(i)$, we have:

$$p(i) = (\sum_{j\in\{c,l,m,k\}}(\delta_j(i)w_j)^{1-\varepsilon_i})^{\frac{1}{1-\varepsilon_i}}. \tag{6}$$

We obtain the demand for factor j in task i conditional on output by plugging in Equations (5) and (6) in (3). By taking the log of the factor demand, we finally have:

$$\mathcal{L}_j(i) \equiv ln(j(i)) = ln(Y) + \varepsilon_i ln(\gamma_j(i)) - \varepsilon_i ln(w_j) + (\varepsilon_i - \sigma)ln(p(i)). \tag{7}$$

Next, I investigate how the demand for inputs changes when these inputs' wages change. Given that minimum wage hikes can affect the wage of different types of employees, it is useful to consider cases where the wage of multiple labor inputs changes. Consistent with the results, I assume that output is unchanged. Due to lack of data, I also assume that the productivity of the inputs at a particular task is constant. When this is the case, the total derivative of the last expression becomes:

$$d\mathcal{L}_j(i) = \underbrace{\varepsilon_i(\frac{dp}{p(i)} - \frac{dw_j}{w_j})}_{\substack{\text{Substitution} \\ \text{within tasks}}} \underbrace{-\sigma\frac{dp}{p(i)}}_{\substack{\text{Substitution} \\ \text{between tasks}}} \;, \tag{8}$$

with $dp = p(i)^{\varepsilon_i}(\sum_{j\in\{c,l,m,k\}} \delta_j(i)^{1-\varepsilon_i} w_j^{-\varepsilon_i} dw_j)$. The first term captures the change in demand for input j in task i due to a change in the relative price of the inputs used in the task. The second term captures the change in demand for input j in task i which stems from a change in demand for task i as the price of that tasks changes relative to other tasks.

Equation (8) demonstrates that the demand for inputs in a given task does not change if the tasks are perfect complements and the inputs used in that task are also perfect complements ($\sigma = 0$ and $\varepsilon_i = 0$). Proposition 1 below considers cases in which tasks are perfect complements, but inputs are not. In these cases, the relationship between inputs in a given task can range from imperfect complements to perfect substitutes. Proposition 2 considers cases in which tasks are more complementary than the inputs within the tasks.[48]

PROPOSITION 1: *Suppose that tasks are perfect complements, but inputs are not ($\sigma = 0$ and $\varepsilon_i > 0$ $\forall i$). In any given task, the demand will increase for*

[48] In these cases tasks can be anything from perfect complements to imperfect substitutes and inputs within tasks can be anything from imperfect complements to perfect substitutes as long as the inputs within the tasks are more substitutable than the tasks themselves. I leave out cases where tasks are less complementary than the inputs within the tasks since this implies that the inputs are more substitutable across tasks than within tasks, which is less realistic.

the input which experiences the smallest percentage increase in wages. On the other hand, the demand for the input with the largest percentage increase in wages will decrease. The change in demand is indeterminate for other inputs in that task. PROOF: see Appendix M.

PROPOSITION 2 : *Suppose that tasks are more complementary than inputs within tasks such that $\sigma \geq 0$, $\sigma < \varepsilon_i \; \forall i$, and $\varepsilon_i > 0 \; \forall i$. In any task using inputs that all become cheaper, the demand will increase for the input that experiences the largest percentage decrease in wages. In tasks using inputs that all become more expensive, the demand for the input with the largest percentage increase in wages will decrease. In tasks using some inputs that become more expensive and some that become cheaper, the demand will increase for the input that experiences the largest percentage decrease in wages, and decrease for the input with the largest percentage increase in wages. The change in demand is indeterminate for other inputs in those tasks.* PROOF: see Appendix M.

If any of the conditions laid out in Propositions 1 and 2 hold, it follows that the demand at the firm level will increase for whichever input experiences the smallest percentage increase in wages among all inputs. Conversely, the demand at the firm level will fall for whichever input experiences the largest percentage increase in wage among all inputs. What happens to inputs with an intermediate wage increase or an intermediate wage decrease is indeterminate. To provide intuition, suppose that the wage of regular workers increases by 2% following a minimum wage hike, and the wage of contract workers increases by 1%, while the wage of other inputs remains unchanged. Regular workers become relatively more expensive than any other input so there is an incentive to substitute away from them in every task. Contract workers become relatively less expensive than regular workers, but relatively more expensive than other inputs. Hence, there is an incentive to substitute towards contract workers in tasks where only regular and contract workers are used. However, in tasks that do not use regular workers, but use a combination of contract workers and some other inputs, there is an incentive to substitute away from contract workers. Therefore, it's not clear what happens to the demand for contract workers at the firm level in this case.

3.1 Discussion and predictions

As the example above illustrates, in order to make predictions, it is necessary to postulate on how the wages of the different inputs evolve following a minimum wage hike. I consider a case in which the wages of both contract workers and regular workers increase following a minimum wage hike. Since the minimum wage is unlikely to be binding for managers, I will assume that their wages are either unchanged or increase relatively less (by a smaller percentage) than those of their subordinates.[49] Karabarbounis and Neiman (2014) study the price of physical capital since the 1980s and find that it has been falling worldwide by at least 0.1 log points annually. I assume that the price of capital falls at this rate and is unaffected by the Indian minimum wage. Finally, due to lack of data, I assume that the wage of offshore labor is constant.

Next, I consider different types of firms and formalize the model's predictions in the context at hand. The predictions are summarized in Table 2.

[49] At the firm level, this means that $\frac{dw_k}{w_k} < \frac{dw_m}{w_m} < \frac{dw_r}{w_r} \lesseqgtr \frac{dw_c}{w_c}$. Below, I consider cases where $\frac{dw_r}{w_r} < \frac{dw_c}{w_c}$ and $\frac{dw_r}{w_r} > \frac{dw_c}{w_c}$ in turn.

Firms not intensive in routine or offshorable tasks

The literature on automation suggests that capital cannot easily replace labor inputs in non-routine tasks. Nevertheless, capital may be used as a perfect (or imperfect) complement to other inputs in certain tasks, and used on its own in other tasks. Following a minimum wage hike, the cost of capital continues to fall at its usual rate, while the cost of other inputs either rises or remains unchanged. Therefore, after such a hike, we would expect no change in the firm-level demand for capital inputs for firms in the average industry if tasks and inputs within tasks are perfect complements, and an increase in the demand for that input otherwise. When regular workers' wages increase by a larger percentage than those of contract workers, there is an incentive to replace regular workers in any task where they are used in tandem with other inputs, as regular workers see the largest wage increase. Therefore, the propositions above imply a decrease in the demand for that input at the firm level. In such a case, the demand for contract workers and managers is indeterminate. If the wage of contract workers increases by a larger proportion, the firm-level demand for contract workers falls, but the change in demand for the other labor inputs is indeterminate.

Firms intensive in routine tasks

Capital is believed to be a better substitute for labor in routine manual tasks and routine analytic tasks. These tasks tend to be performed by low and intermediate skill workers, respectively (see Acemoglu and Autor (2011) and Autor and Dorn (2013)). As mentioned, contract workers are generally less skilled than regular workers, who are in turn presumably less skilled than

Table 2: Summary of predictions

Average Industries		Routine Industries		Offshorable Industries	
$dw_{reg}/w_{reg} > dw_{cont}/w_{cont}$	$dw_{reg}/w_{reg} > dw_{cont}/w_{cont}$	$dw_{reg}/w_{reg} > dw_{cont}/w_{cont}$	$dw_{reg}/w_{reg} > dw_{cont}/w_{cont}$	$dw_{reg}/w_{reg} > dw_{cont}/w_{cont}$	$dw_{reg}/w_{reg} > dw_{cont}/w_{cont}$
$dX_k \geq 0$	$dX_k \geq 0$	$dX_k > 0$	$dX_k > 0$	dX_k ?	dX_k ?
$dX_{reg} < 0$	dX_{reg} ?	$dX_{reg} < 0$	dX_{reg} ?	$dX_{reg} < 0$	dX_{reg} ?
dX_{cont} ?	$dX_{cont} < 0$	dX_{cont} ?	$dX_{cont} < 0$	dX_{cont} ?	$dX_{cont} < 0$
dX_{man} ?	dX_{man} ?	dX_{man} ?	dX_{man} ?	dX_{man} ?	dX_{man} ?
				$dX_{k_o} \geq 0$	$dX_{k_o} \geq 0$
				$dX_{l_o} > 0$	$dX_{l_o} > 0$

Note: dw_j/w_j represents the percentage change in wage for input j. The question marks indicate an indeterminate sign. dX_j represents the change in demand for input j at the firm level. The inputs are abreviated as follows: regular workers $\rightarrow$ reg, contract workers $\rightarrow$ cont, managers $\rightarrow$ man, capital $\rightarrow$ k, offshore capital $\rightarrow$ k_o, and offshore labor $\rightarrow$ l_0.

managers. Hence, capital is more likely to be a substitute in certain tasks done by contract and/or regular workers. As a result, when firms are intensive in routine tasks, we would expect a clear increase in capital at the firm level following a minimum wage hike. When the wage of regular workers increases by a larger percentage than the wage of contract workers following a minimum wage hike, the former group will be in lower demand for routine tasks and the demand for contract workers may either fall, or remain the same, in other tasks, depending on input complementarity in these tasks. As a result, demand for regular workers is expected to fall at the firm level. The effect for managers remains undetermined. When the wage of contract workers increases by the largest percentage, it is the demand for these workers that is expected to fall, while the effect on demand for other labor inputs in unclear.

Firms intensive in offshorable tasks

Tasks that require fewer face-to-face interactions and that do not need to be performed in a specific location, like data analysis, call-based or online customer support, and programming are easier to offshore. These tasks are usually analytic rather than manual, and are more likely to be performed by a combination of regular workers and information technology. Therefore, a more appropriate functional form for these tasks could be:

$$y(i) = (min[\delta_l l(i),\ \delta_k k(i)]^{\frac{\varepsilon_i - 1}{\varepsilon_i}} + min[\delta_{l_o} l_o(i),\ \delta_{k_o} k_o(i)]^{\frac{\varepsilon_i - 1}{\varepsilon_i}})^{\frac{\varepsilon_i}{\varepsilon_i - 1}},$$

where l_o and k_o are labor and capital offshore, respectively. $\delta_l > 0$ and $\delta_k > 0$ if capital is used in these tasks, and ε_i increases when it is easier to offshore the task. In this case, the input demand at the task level is driven by the relative cost of the labor-capital bundle in India to the cost of the bundle offshore. Otherwise, the analysis and its conclusion remain the same. That is, the more offshorable the tasks are, the more likely it is that Indian inputs for these tasks will be replaced by inputs offshore following a minimum wage hike in India. As a result, we would expect to see an aggregate increase in the usage of inputs offshore by Indian firms more intensive in offshorable tasks. The demand for Indian inputs in these tasks would fall as a result. As explained before, the demand for capital inputs in other tasks is predicted to increase or remain unchanged. Therefore, the net change in capital used in India is unclear at the firm level. Like before, when regular workers become more expensive than contract workers, the demand for regular workers in offshorable tasks and other tasks falls. Hence, we would expect a drop in the demand for regular workers in India at the firm level in this case. When contract workers become more expensive than regular workers following a minimum wage change, the demand for contract workers in India decreases. However, it is unclear how the demand for regular workers will change in India. On the one hand, there is less demand for them in offshorable tasks. On the other hand, firms have an incentive to substitute contract workers with regular workers in tasks where both of these inputs are used.

4 Empirical strategy

To test whether increases in minimum wages have an effect on capital investment and employment, I adopt a difference-in-difference approach; I compare the adjustment in investment and employment of firms experiencing a minimum wage increase to that of firms that do not experience a hike, before and after the minimum wage increase. This "panel approach" uses variation from all firms in the data, and is prevalent in the minimum wage literature (see Neumark and Wascher (1992, 2007), and Neumark (2019) for a summary). An alternative "contiguous design" approach consists of comparing firms exposed to a minimum wage increase located in districts along state lines to firms in contiguous districts of the neighboring states.[50] Both approaches have advantages and potential pitfalls. The contiguous design rests on the idea that firms along state lines are more likely to evolve in similar economic environments. However, it is more susceptible to bias if there is movement of firms or workers across state lines due to the changing minimum wage. Moreover, this approach can introduce artificial variation. Since contiguous districts are paired, obser-

[50] See Card and Krueger (2000), Dube et al. (2010), Allegretto et al. (2011), Soundararajan (2019), Coviello et al. (2021)

vations are duplicated for districts that share a border with more than one other district across state lines. However, the panel approach is more robust to migration as it does not rely only on observations along state lines, but can compare firms that may evolve in dissimilar environments.

Given the benefits and pitfalls of both strategies, I show results of the panel regression approach in the main body of the essay, and show that the results are robust to using the contiguous design in Appendix F. The reason for focusing on the panel approach is two-fold. The first reason is that I include district-by-year fixed effects that account for district-specific shocks. Hence, the critique that firms in border districts may evolve in more similar environments is less relevant in this context. The second reason comes from data constraints. To identify contiguous districts, I used shape files that use administrative codes for the districts. The ASI data also uses the administrative district codes, but the Prowess dataset uses its own code to classify districts. To identify neighboring districts in that dataset, I map the district names from the shape files to the district names in Prowess. However, this mapping is imperfect, which forces me to drop many firm-year observations.

For the main analysis, I estimate the following regression for the investment outcomes:

$$y_{fsdit} = \alpha + \eta M_{sit} + \boldsymbol{X}_{fsit}\beta + \Phi + \varepsilon_{fsdit}, \tag{9}$$

where y is the dependent variable for firm f, in state s, district d, and 4-digit industry i in year t. M is the real minimum wage in that state and industry that year. The matrix $\boldsymbol{X}$ contains the firm level time varying predictors of capital investment mentioned in Subsection 2.2 and Φ is a matrix of fixed effects. I include firm, district-by-year, and 4-digit-industry-by-year fixed effects. The first absorbs time-invariant firm-level characteristics. Firm fixed effects imply that I make use of within-firm variation, essentially comparing the same firm exposed to different levels of minimum wage. The final two sets of fixed effects account for idiosyncratic time trends within districts and within industries. This unusual level of granularity for time trends in a minimum wage regression alleviates some concerns with the panel approach since it accounts for differences in the evolution of economic environments across districts and industries. It also helps with concerns that are usually present when the minimum wage changes only at a higher administrative level such, as at the state level in the U.S. When this is the case, it is hard to distinguish the effect of minimum wage hikes from other confounding statewide policies.

To capture heterogeneity in the effect of minimum wage hikes, I interact the real industry minimum wage with the routineness (R_i) and offshorability intensity (O_i) of industries as follows:

$$y_{fsdit} = \alpha + \eta_0 M_{sit} + \eta_1 M_{sit} R_i + \eta_2 M_{sit} O_i + \beta X_{fsdit} + \Phi + \varepsilon_{fsdit} \tag{10}$$

Note that the time-invariant terms are absorbed by the fixed effects. I estimate the same regressions for the employment variables from the ASI data, where each term, other than the fixed effects, is further interacted with the type of worker (regular workers, contract workers, and managerial workers).[51] For the investment regressions, all firms with a positive amount of capital for some

[51] All employment regressions use sampling weights. Given the unbalanced nature of the ASI data, I include the same fixed effects as in the investment regressions, but no controls in the main analysis of the employment outcomes.

years of the study period are included. This way, the same firms are included in all investment regressions. Similarly for the employment regressions, firms with any number of paid adult employees for some years are included.[52]

In all regressions, standard errors are clustered at the 4-digit-industry-by-state level.[53] The identification of the coefficients in the regressions requires that conditional on the controls and fixed effects, there are no differences in pretrends, and that no other policy or event at the same level of variation occur simultaneously. Controlling for industry-by-year and district-by-year fixed effects accounts for differences in the dependent variable due to observed and unobserved differences between districts and industries. The fixed effects also account for policies occurring at the level of observation such as the NREGA roll- out explained in Subsection 2.1. I further use a distributed lag specification and produce event-study graphs to show that there is little evidence of pretrends in the present context. Another threat to identification can occur if firms or workers move due to minimum wage hikes. While this is a possibility, wage-induced worker migration, both in absolute and relative terms, is known to be very low in India (Klasen and Pieters (2015), Munshi and Rosenzweig (2016), Menon and Rodgers (2017)). Moreover, since I am leveraging within-firm variation, movements of firms should not affect the estimates (Coviello et al. (2021)).

Following Freyaldenhoven et al. (2019), the distributed lag analogue of Equation (9) with two pre-event and four post-event periods can be written

[52]For example, if a firm does not have contract workers for some years, then the number of contract workers for that firm is coded as 0 for those years. The ASI is cross-sectional by design, but since I am interested in within-firm adjustment, I restrict my attention to firms that are surveyed at least twice during the study period allowing for the inclusion of firm fixed effects.

[53]The significance levels change little if I use one cluster for states and one cluster for industries. The same is true if I cluster at the 4-digit-industry-by-district level, but the number of observations per cluster can be small. Therefore, the preferred clustering strategy is more sensible.

as:

$$y_{fsdit} = \alpha + \eta_{-2} M_{sit+2} + \sum_{s=-1}^{3} \eta_s \Delta M_{sit-s+1} + \eta_4 M_{sit-4} + \boldsymbol{X}_{fsdit}\beta + \Phi + \varepsilon_{fsdit}, \quad (11)$$

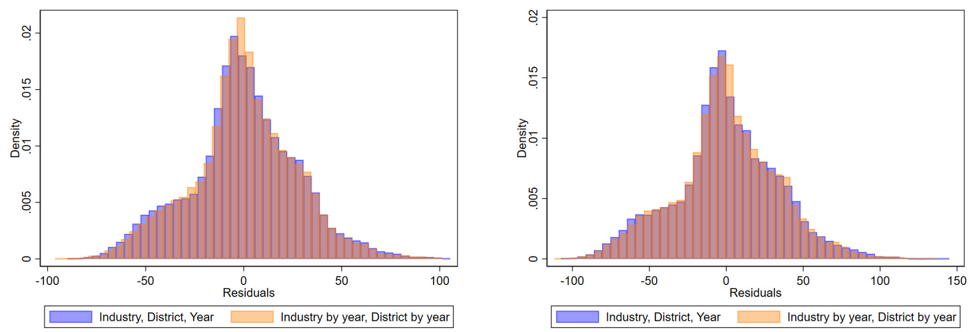
where M_{sit+2} is the second minimum wage lead, M_{sit-4} is the fourth lag, and $\Delta M_{sit-s+1}$ is the difference in the real minimum wage between two consecutive years. For example, if $s = -1$, then ΔM_{sit+2} is the difference between the second and first lead of the minimum wage. The analogue to Equation (10) is obtained by interacting each minimum wage term with the RTI and offshorability indexes.[54]

Before moving on to the results, it is important to assess whether the granular fixed effects soak up all the variation in minimum wages. To do so, I regress those wages on the fixed effects, and plot the distribution of residuals in Figure 3. Blue indicates the distribution of the residuals when state, year, and industry fixed effects are included. Orange indicates the distribution of residuals when industry-by-year and district-by-year fixed effects are included instead. As shown, plenty of variation in the residual wages remains after including the more stringent and preferred fixed effects. This is true both for the nominal wages in Panel (a), and the real wages in Panel (b).

[54]The data sample consists of 7 years. Therefore, I set the minimum wage leads and lags equal to the last available data point. This ensures that no firm is dropped for this exercise.

Figure 3: Variation in residuals

(a) Nominal Minimum Wages (b) Real Minimum Wages



Note: I use the ASI dataset and regress the nominal and real minimum wages on industry, district, and year fixed effects in Panel (a). I regress the wages on industry-by-year and district-by-year fixed effects in Panel (b).

5 Results

5.1 Capital Investment

In this subsection, I investigate firms' capital investment responses following changes in minimum wages. I first present evidence of adjustment in overall capital in Table 3. The first column corresponds to Equation (9) and captures the average effect of a minimum wage hike across all firms. Column (2) presents the heterogeneous effects of the minimum wage across firms differing in their routineness intensity unconditional on offshorability. Column (3), does the same for offshorability unconditional on routineness intensity. The preferred specification can be found in Column (4) corresponding to Equation (10) where the heterogeneous effects due to differences in routineness and offshorability intensity are analyzed in tandem. The routineness and offshorability indexes are measured in standard deviations from the mean. Hence, the first coefficient in Columns (2) to (4) captures the effect for firms in the average industry. Each coefficient can be interpreted as a 1 percentage point change in the dependent variable.

The first thing to notice from Table 3 is that ignoring heterogeneity across industries would lead us to conclude that minimum wages have little effect on capital investment, as shown by the small and insignificant coefficient in Column (1). Comparing Columns (2) and (3) to Column (4) indicates that routineness intensity is the more important driver of heterogeneity in capital investment across firms, following a minimum wage hike. All else equal, the results from the preferred specification indicate that firms in industries more routine-intensive by 1 standard deviation above the mean increase their capital investment by 0.8 percentage points following a typical increase in the real minimum wage (2.5 rupees).[55] This represents an increase of 6.5% given that firms invest at a rate of 12.3% on average. Instead, firms in the average industry continue to invest in capital expenditures at their usual rate. The point estimate suggests that firms in industries more intensive in offshorable tasks reduce overall capital investment by about 4.9% (0.6 percentage point) following a typical minimum wage increase.

[55] $(\beta_1 + \beta_2) \times 2.5 = 0.64$ where 2.5 rupees is a typical increase in the real minimum wage.

Table 3: Effect of a minimum wage increase on overall capital investment

	Capital			
	(1)	(2)	(3)	(4)
Minimum wage	-0.00742	-0.0797	-0.000153	-0.0773
	(0.0484)	(0.0514)	(0.0514)	(0.0501)
Minimum wage X RTI		0.320**		0.392***
		(0.126)		(0.142)
Minimum wage X Offshore			-0.0651	-0.167
			(0.115)	(0.121)
Observations	54997	54997	54997	54997
Mean of Y	12.29	12.29	12.29	12.29
SD	68.30	68.30	68.30	68.30

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress investment on real minimum wages in Column (1). I also include the interaction between the real minimum wages and the routineness index in Column (2). In Column (3), I include the interaction between the real minimum wages and the index of offshorability. Column (4) is the preferred specification and includes both interactions. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. All specifications include fourth-degree polynomials in age, lagged revenue, lagged profit margin, and revenue growth. Standard errors are clustered at the four-digit-industry-by-state level. The largest 2.5% and smallest 1% of values of the dependent variable are winsorized. All firms with positive net value in machinery and/or computers for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

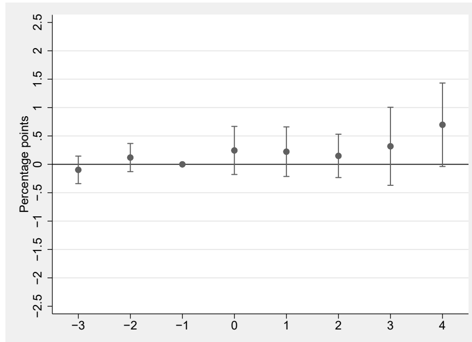
Figure 4 presents the event study results for overall capital investment. The effect of an increase in the real minimum wage on the rate of investment for firms in the average industry are presented in Panel (a), for firms in more routine-intensive industries in Panel (b), and for firms in industries intensive in offshorable tasks in Panel (c).[56] The graphs present 90% confidence bands. As shown in this figure, there is little evidence of pretrend differences, and the

[56]Firms in more routine-intensive industries refer to firms in industries more routine intensive by 1 SD, holding offshorability at the mean (RTI=1 and Offshorability=0). Similarly, firms in industries intensive in offshorable tasks are firms in industries where the offshorability index is 1 SD above the mean, all else equal (RTI=0 and Offshorability=1).

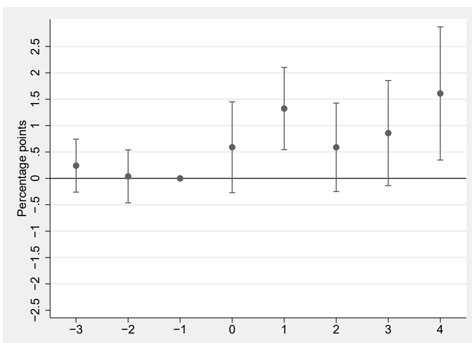
graphs reflect the findings above, but with some nuance. Panels (a) and (c) indicate that firms in the average industry and firms in industries more intensive in offshorable tasks see no meaningful changes in their rate of investment following a wage hike. As I present below, this latter group of firms tends to see a reduction in computer investment, but not so much in machinery. Panel (b) shows that firms in routine industries increase their investment in capital shortly after the increase in the minimum wage, and continue to increase investment for multiple periods after the wage change. This indicates that minimum wage hikes do not lead to a one-time lump increase in capital, but to repeated increases over time.

Figure 4: Event study of a minimum wage increase on overall capital investment

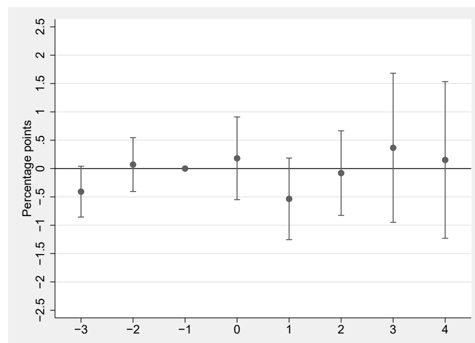
(a) Firms in the average industry



(b) Firms in in industries intensive in routine tasks



(c) Firms in industries intensive in offshorable tasks



Note: 90% confidence bands are displayed. I regress investment on 2 leads and 4 lags of the real minimum wages (see Equation 11). I also include an interaction of each of the minimum wage coefficient with the routineness and offshorability indexes, separately. I report the coefficients of the regression for a typical minimum wage hike (2.5 rupees). In Panel (a), I show the results when the routineness and offshorability indexes are at the mean (when they are equal to 0). In Panel (b), I report the results when the routineness intensity index is one SD above the mean (the offshorability index is kept at the mean). In Panel (c), I report the results when the offshorability intensity index is one SD above the mean (the routineness index is kept at the mean). All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. All specifications include fourth-degree polynomials in age, lagged revenue, lagged profit margin, and revenue growth. Standard errors are clustered at the four-digit-industry-by-state level. The largest 2.5% and smallest 1% of values of the dependent variable are winsorized. All firms with positive net value in machinery and/or computers for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Next, I investigate the effect of a hike on the two components of capital investment. In Table 4 and Figure 5, I examine how firms adjust their investment in machinery. Firms in the average industry, or in more offshorable industries, see little change in machinery investment, as shown in Figure 4. However, firms in more routine industries see a 6.1% (0.5 percentage points) increase in machinery investment for a usual increase in the minimum wage in their industry (2.5 rupees).

Table 4: Effect of a minimum wage increase on investment in machinery

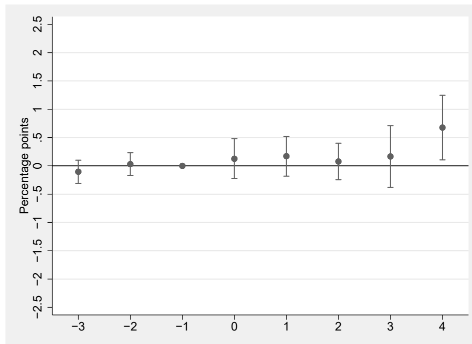
	Machinery			
	(1)	(2)	(3)	(4)
Minimum wage	-0.0154	-0.0635	-0.0123	-0.0621
	(0.0417)	(0.0446)	(0.0440)	(0.0436)
Minimum wage X RTI		0.213*		0.253**
		(0.110)		(0.124)
Minimum wage X Offshore			-0.0283	-0.0943
			(0.0965)	(0.104)
Observations	54997	54997	54997	54997
Mean of Y	7.761	7.761	7.761	7.761
SD	49.27	49.27	49.27	49.27

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress investment on real minimum wages in Column (1). I also include the interaction between the real minimum wages and the routineness index in Column (2). In Column (3), I include the interaction between the real minimum wages and the index of offshorability. Column (4) is the preferred specification and includes both interactions. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 2.5% and smallest 1% of values of the dependent variable are winsorized. All firms with positive net value in machinery and/or computers for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

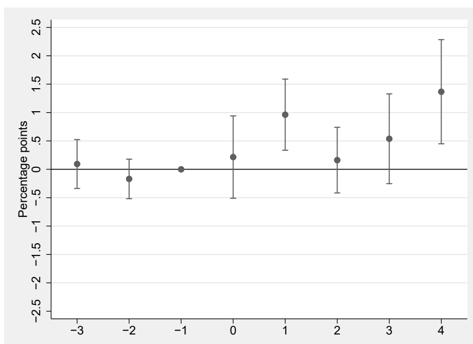
Figure 5 is also similar to Figure 4 in both magnitude and the periods at which the rate of investment changes. Just like before, there is little evidence of preexisting trends. Firms in routine-intensive industries see an increase in machinery investment shortly after the wage hike, and the rate of investment is sustained for multiple periods.

Figure 5: Event study of a minimum wage increase on investment in machinery

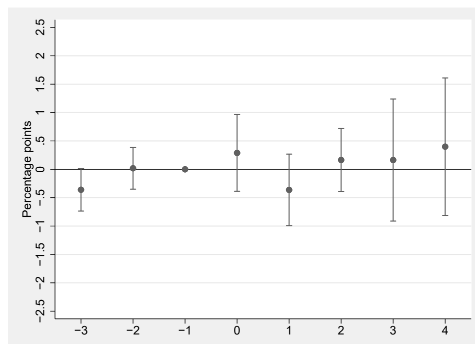
(a) Firms in the average industry



(b) Firms in in industries intensive in routine tasks



(c) Firms in industries intensive in offshorable tasks



Note: 90% confidence bands are displayed. I regress machinery investment on 2 leads and 4 lags of the real minimum wages (see Equation 11). I also include an interaction of each of the minimum wage coefficient with the routineness and offshorability indexes, separately. I report the coefficients of the regression for a typical minimum wage hike (2.5 rupees). In Panel (a), I show the results when the routineness and offshorability indexes are at the mean (when they are equal to 0). In Panel (b), I report the results when the routineness intensity index is one SD above the mean (the offshorability index is kept at the mean). In Panel (c), I report the results when the offshorability intensity index is one SD above the mean (the routineness index is kept at the mean). All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. All specifications include fourth-degree polynomials in age, lagged revenue, lagged profit margin, and revenue growth. Standard errors are clustered at the four-digit-industry-by-state level. The largest 2.5% and smallest 1% of values of the dependent variable are winsorized. All firms with positive net value in machinery and/or computers for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table 5 and Figure 6 present the investment responses for computers. The table indicates that firms in more routine-intensive industries see a 0.35 percentage point (or a 4% increase) in computer investment following a typical minimum wage hike. While the point estimate is not statistically significant, the figure below also points towards an increase in computer investment for these firms. Instead, firms more intensive in offshorable tasks see a 6.2% decline (0.5 percentage points) in computer investment following a typical hike.

Table 5: Effect of a minimum wage increase on investment in computers

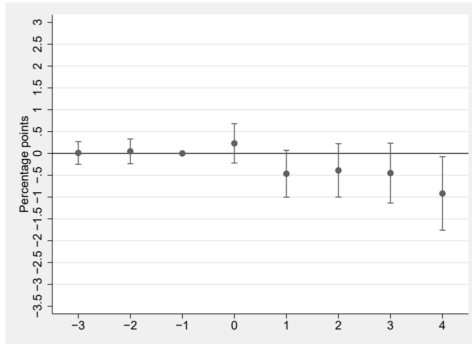
	Computers			
	(1)	(2)	(3)	(4)
Minimum wage	-0.0341	-0.0671	-0.0244	-0.0651
	(0.0359)	(0.0476)	(0.0380)	(0.0464)
Minimum wage X RTI		0.146		0.207
		(0.138)		(0.145)
Minimum wage X Offshore			-0.0870	-0.141
			(0.0857)	(0.0872)
Observations	54997	54997	54997	54997
Mean of Y	8.332	8.332	8.332	8.332
SD	66.00	66.00	66.00	66.00

Note: 90% confidence bands are displayed. I regress investment on real minimum wages in Column (1). I also include the interaction between the real minimum wages and the routineness index in Column (2). In Column (3), I include the interaction between the real minimum wages and the index of offshorability. Column (4) is the preferred specification and includes both interactions. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. All specifications include fourth-degree polynomials in age, lagged revenue, lagged profit margin, and revenue growth The largest 2.5% and smallest 1% of values of the dependent variable are winsorized. All firms with positive net value in machinery and/or computers for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

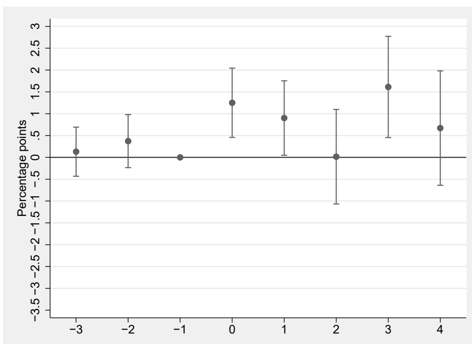
Panel (a) of Figure 6 suggests that firms in the average industry may increase their investment during the year that the minimum wage increases, and reduce their investment afterwards. This indicates that investment may fall relative to similar firms that are not exposed to a minimum wage hike. Panel (b) indicates that firms intensive in routine tasks see an increase in computer investment soon after a minimum wage hike, and the increase continues for ensuing periods. On the other hand, firms in more offshorable industries see a decrease in computer investment soon after the hike, and also continue to do so for multiple years.

Figure 6: Event study of a minimum wage increase on investment in computers

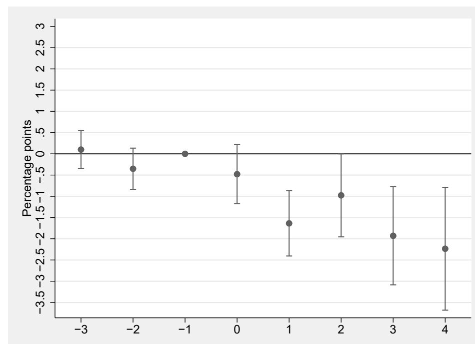
(a) Firms in the average industry



(b) Firms in in industries intensive in routine tasks



(c) Firms in industries intensive in offshorable tasks



Note: 90% confidence bands are displayed. I regress computer investment on 2 leads and 4 lags of the real minimum wages (see Equation 11). I also include an interaction of each of the minimum wage coefficient with the routineness and offshorability indexes, separately. I report the coefficients of the regression for a typical minimum wage hike (2.5 rupees). In Panel (a), I show the results when the routineness and offshorability indexes are at the mean (when they are equal to 0). In Panel (b), I report the results when the routineness intensity index is one SD above the mean (the offshorability index is kept at the mean). In Panel (c), I report the results when the offshorability intensity index is one SD above the mean (the routineness index is kept at the mean). All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. All specifications include fourth-degree polynomials in age, lagged revenue, lagged profit margin, and revenue growth. Standard errors are clustered at the four-digit-industry-by-state level. The largest 2.5% and smallest 1% of values of the dependent variable are winsorized. All firms with positive net value in machinery and/or computers for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

The results presented above indicate that changes in minimum wages lead firms in industries intensive in routine occupations to increase their investment in machinery and computers. If labor falls or remains unchanged, such an uptake in investment would suggest that firms more intensive in routine tasks set themselves on a mechanization/automation path following increases in labor costs. Firms intensive in offshorable occupations instead see a fall in their rate of investment in computers and related IT equipment. On the other hand, firms in industries that are intensive in neither routine nor offshorable tasks see little adjustment in capital.

Table 6: Effect of a minimum wage increase on profit margin

	Profit Margin	
	(1)	(2)
Minimum wage	0.0150	0.0183
	(0.00922)	(0.0130)
Minimum wage X RTI		-0.0351
		(0.0356)
Minimum wage X Offshore		0.0414
		(0.0305)
Observations	54997	54997
Mean of Y	2.093	2.093
SD	18.79	18.79

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress the profit margin on real minimum wages in Column (1). I also include the interaction between the real minimum wages and the routineness index and the interaction between the real minimum wages and the index of offshorability in Column (2). All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. All specifications include fourth-degree polynomials in age, lagged revenue, lagged profit margin, and revenue growth. Standard errors are clustered at the four-digit-industry-by-state level. The largest and smallest 7.5% of values of the dependent variable are winsorized due high variation in this variable. All firms with positive net value in machinery and/or computers for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

In order to get a more complete picture of firm adjustments, it is important to investigate what happens to labor at the firm level.[57] Labor employment comes from the ASI data and will be tackled in the next section. Before moving on to employment responses, I make one final use of the Prowess data to study what happens to firms' profit margins and output growth following a minimum wage hike. Table 6 reports the results for firms' profit margins and indicates

[57]As mentioned earlier, I obtained employment information from the ASI which only includes firms from manufacturing industries, while the investment results above include firms from all industries. The results above are similar in sign and magnitude when focusing on the manufacturing industries.

that profits are mostly unaffected by rising minimum wages.[58] In Table 7, I investigate whether changes to the minimum wages impact output growth, as measured by the growth in the sales of the goods produced and services offered by the firms.[59] Similar to the profit margin results, all coefficients are small in magnitude and statistically insignificant. This suggests that the firms' adjustments ensure that their bottom line is not altered by minimum wage regulations.

[58]The profit margin is defined as the percentage of profit that a firm generates from the total income it made in a year, after expenses, but before paying direct taxes (see Appendix B for additional details).

[59]This variable is computed in a fashion similar to the investment variables. I take the difference in gross sales of the output over the year and divide it by the average value of the gross sales at the beginning and end of the previous year.

Table 7: Effect of a minimum wage increase on the output growth

	Output Growth	
	(1)	(2)
Minimum wage	-0.00932	-0.00901
	(0.0113)	(0.0162)
Minimum wage X RTI		-0.0178
		(0.0446)
Minimum wage X Offshore		0.0332
		(0.0335)
Observations	54997	54997
Mean of Y	7.798	7.798
SD	18.09	18.09

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress the growth in the sales of the goods produced and services offered by the firms on real minimum wages in Column (1). I also include the interaction between the real minimum wages and the routineness index and the interaction between the real minimum wages and the index of offshorability in Column (2). All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. All specifications include fourth-degree polynomials in age, lagged revenue, lagged profit margin, and revenue growth. Standard errors are clustered at the four-digit-industry-by-state level. The largest and smallest 5% of values of the dependent variable are winsorized. All firms with positive net value in machinery and/or computers for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

5.2 Employment

Next, using data from ASI, I investigate how firms adjust their labor inputs when the minimum wages evolve. Table D.1 in Appendix D shows the results for the average number of employees working during a typical 8-hour workday for different categories of employees, namely regular workers, contract workers, and managers. Table D.2 does the same for the total number of mandays worked during the year for every type of employee. In the tables, the main coefficients are interacted with the type of employee, with regular workers being the excluded type. This facilitates comparisons between these groups, and suggests that minimum wage hikes have stronger employment effects for non-routine firms. However, the number of interaction terms in the tables make it harder to distinguish the total effects of the minimum wage increases. In the Tables H.5 and H.7, I compute the total effects for a typical hike in minimum wages (2.5 rupees) for each category of employee for firms in the average industry, and for firms in industries more routine intensive, by one standard deviation, and for firms in industries more offshorable by one SD.[60] The results in Tables H.5 and H.7 are similar in magnitude and significance.

Similar to capital investment, ignoring heterogeneity across firms would lead to a conclusion that minimum wages have no discernible effects on how firms adjust their labor inputs. Column (1) of Tables H.5 and H.7 captures the effect of an increase in the minimum wage for firms across all manufacturing industries, while allowing for heterogeneous effects based on the routineness and offshorability of the different industries.

[60] For example, holding offshorability at it's mean value of 0, the total effect of an increase for contract workers in industries more routine by 1 SD is $2.5 * (\beta_1 + \beta_2 + \beta_4 + \beta_5)$ where β_j represents the j^{th} coefficient of a given column in Table D.1.

Table 8: Total effect of a minimum wage increase on the number of employees working in a typical workday

	(1) Pooled	(2) Group 1	(3) Group 2	(4) Group 3	(5) Group 4
		Median firm compensation < 105% of minwage	Median firm compensation [105%, 130%) of minwage	Median firm compensation [130%, 180%) of minwage	Median firm compensation > 180% of minwage
Minimum wage	-.03	-.82***	-.15*	-.13	.29***
	(.052)	(.251)	(.088)	(.091)	(.081)
MinXContract	.06	.52***	.09	.11	-.01
	(.04)	(.157)	(.063)	(.071)	(.048)
MinXManager	-.04*	.41***	.01	-.08*	-.15***
	(.025)	(.12)	(.043)	(.043)	(.043)
MinXRTI	.45***	-.44*	.29*	.63***	.5***
	(.135)	(.258)	(.17)	(.271)	(.164)
MinXRTIXContract	-.27***	.31*	-.09	-.34**	-.32***
	(.082)	(.181)	(.125)	(.153)	(.105)
MinXRTIXManager	-.25***	.26**	-.12	-.39***	-.34***
	(.062)	(.13)	(.084)	(.106)	(.083)
MinXOff	-.45***	-1.2***	-.76***	-.46***	-.23
	(.124)	(.258)	(.214)	(.164)	(.183)
MinXOffXContract	.4***	.68***	.35**	.27**	.38***
	(.081)	(.177)	(.153)	(.12)	(.116)
MinXOffXManager	.24***	.53***	.21**	.01	.21***
	(.059)	(.148)	(.102)	(.085)	(.086)
Observations	420051	42270	45483	84618	244998
Mean of Y	39.59	36.44	30.74	44.88	40.17
SD	76.50	76.34	67.74	85.37	74.97

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress the number of employees working during a typical 8-hour workday on the real minimum wages and the interaction between these wages and the routineness and offshorability indexes. Each variable is further interacted with the type of employee, namely, contract workers and managers. Regular workers are the excluded type of employee. I compute the total effect of a typical real minimum wage increase of 2.5 rupee for each type of employee. Column (1) reports the results for all firms. Columns (2)-(5) report the results for firms in the first-fourth compensation groups, respectively. For every district, industry, year, I compute the median compensation per day across firms for regular workers and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample. Columns (2)-(5) reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%, between 105 and 130%, between 130 and 180%, and above 180% of the average minimum wage in the district over the study period, respectively. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% of values of the dependent variable are winsorized. All firms with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

The first 3 coefficients in Column (1) of both tables are small and mostly insignificant suggesting that firms in the average industry do little or no adjustment to labor inputs following a change in the wages. Instead, firms in industries intensive in offshorable tasks substitute away from regular workers in favor of managers and contract workers. On the other hand, the results suggest that firms in more routine-intensive industries by one SD above the mean employ 0.45 additional regular workers, while employing about 0.3 fewer contract workers and managers following a hike. These latter results and the lack of adjustment for firms in the average industry are somewhat puzzling at first glance and warrants further investigation.

The ASI contains data on the total compensation bill paid to different groups of employees. This includes wages, salaries, overtime pay, paid leave including holidays, allowances, and bonuses, among other expenses, before taxes and insurance contributions. I divide this variable by the number of mandays worked by each employee group to derive an estimate of the compensation bill for a typical employee, expressed in rupees per day. For every district, industry, and year, I compute the median daily compensation across firms for regular workers, and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample.

In Columns (2) to (5), I look at firms in different compensation groups. I examine firms in districts and industries where the median firm-level compensation paid to regular workers is less than 105%, between 105% and 130%, between 130% and 180%, and above 180% of the average minimum wage in their district and industry over the study period.[61] The idea behind this exercise is that the closer regular workers' compensation is to the minimum wage, the more likely their wages will increase with a minimum wage hike.

[61] I chose the cutoffs such that approximately 25% of all industry-districts with some non-zero minimum wages fall into each compensation group. Then, I winsorize the top 5% of values of the ratio. I use only non-zero minimum wages when computing the average minimum wage. Firms in industry-states without minimum wages receive the highest ratios after winsorizing. Therefore, these firms fall into the last compensation group. Including a dummy for whether firms are in an industry, and state where the minimum wage increases from 0 to a positive value during the study period, and a dummy for whether firms are in industries and states without a minimum wage throughout the study period, has a negligible effects on the regressions. The regressions are also robust to excluding firms in industries and states lacking a minimum wage throughout the study period.

Table 9: Total effect of a minimum wage increase on the number of mandays

	(1) Pooled	(2) Group 1	(3) Group 2	(4) Group 3	(5) Group 4
		Median firm compensation < 105% of minwage	Median firm compensation [105%, 130%) of minwage	Median firm compensation [130%, 180%) of minwage	Median firm compensation > 180% of minwage
Minimum wage	-9.11	-210.18***	-33.2	-40.1	79.31***
	(13.983)	(58.748)	(26.146)	(26.865)	(20.06)
MinXContract	11.96	124.49***	21.17	25.61	.5
	(9.993)	(39.311)	(16.856)	(18.997)	(12.263)
MinXManager	-8.73	96.19***	7.87	-23.71*	-39.74***
	(6.887)	(30.265)	(12.971)	(13.103)	(11.182)
MinXRTI	132.02***	-118.63*	111.29**	188.44***	141.6***
	(40.294)	(68.629)	(53.424)	(81.025)	(47.957)
MinXRTIXContract	-78.67***	55.9	-27.61	-105.97**	-90.59***
	(23.894)	(51.376)	(37.065)	(45.794)	(30.983)
MinXRTIXManager	-73.75***	39.88	-33.34	-120.12***	-99.01***
	(18.283)	(37.055)	(26.817)	(32.862)	(24.246)
MinXOff	-147.83***	-338.89***	-248.29***	-138.99***	-89.93*
	(38.79)	(67.991)	(72.602)	(51.815)	(52.527)
MinXOffXContract	119.93***	177.07***	93.37*	82.54***	127.98***
	(24.711)	(49.318)	(48.974)	(34.952)	(33.775)
MinXOffXManager	84.69***	135.04***	64.57*	14.99	79.98***
	(18.142)	(41.63)	(35.225)	(26.128)	(23.851)
Observations	420051	42270	45483	84618	244998
Mean of Y	11690.0	9926.0	8950.9	13563.5	11929.5
SD	23067.7	21719.8	20604.9	26111.5	22634.2

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress the number of 8-hour workdays paid to each group of employee over the year on the real minimum wages and the interaction between these wages and the routineness and offshorability indexes. Each variable is further interacted with the type of employee, namely, contract workers and managers. Regular workers are the excluded type of employee. I compute the total effect of a typical real minimum wage increase of 2.5 rupee for each type of employee. Column (1) reports the results for all firms. Columns (2)-(5) report the results for firms in the first-fourth compensation groups, respectively. For every district, industry, year, I compute the median compensation per day across firms for regular workers and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample. Columns (2)-(5) reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%, between 105 and 130%, between 130 and 180%, and above 180% of the average minimum wage in the district over the study period, respectively. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% of values of the dependent variable are winsorized. All firms with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Looking at firms in different compensation groups sheds light on the effect of a minimum wage increase on how firms switch between types of employees.[62] I find that firms in the first compensation group which are intensive in neither routine nor offshorable tasks have 0.82 fewer regular workers on a typical workday (equivalent to a reduction of 210 mandays for this group over the year), but 0.52 and 0.41 additional contract workers and managers following a minimum wage hike (124 and 96 additional mandays). Firms in routine-intensive industries in this compensation group employ 0.44 fewer regular workers after a minimum wage increase (118 fewer mandays). For this group of firms, the evidence of substitution towards other workers is not as strong. Table H.5 suggests that routine intensive firms employ approximately 0.3 additional contract workers and managers following a typical minimum wage hike, corresponding to 56 and 40 additional mandays throughout the year for contract workers and managers, respectively. However, the estimates for the number of workdays paid to these two types of employees are far from significant. Taken together with the investment results, this suggests that routine intensive firms substitute regular workers in a large part for capital inputs. Firms intensive in offshorable tasks employ 1.2 fewer regular workers (339 fewer mandays), while the number of contract workers and managers increases by 0.68 and 0.53 (177 and 135 additional mandays), respectively.

Moving to the latter compensation groups, substitution away from regular workers weakens for all types of firms. For both firms in the average indus-

[62] As mentioned before, Prowess uses its own district codes, while other datasets use the district administrative codes. This introduces imperfections into the mapping. Moreover, many firms in the Prowess dataset are located in districts that are not in the ASI. As a result, I do not replicate the compensation heterogeneity analysis for the investment outcomes, since bringing the compensation measures to the Prowess dataset significantly cuts the sample of firms.

try and firms in more routine-intensive industries, the substitution patterns eventually reverse. In the highest compensation group, firms in the average industry experience a small increase in regular workers employed on a typical 8-hour workday. This pattern also appears in more routine-intensive firms. For example, the number of regular workers employed per workday increases by 0.5-0.63 workers, and this time, the number of contract workers and managers falls by approximately 0.3-0.4 employees in compensation groups 3 and 4.

To understand the sign reversal in the latter compensation groups, it is helpful to investigate the relationship between regular workers' compensation and that of contract workers. Using all firms that employ both types of workers, I compute the average within-firm ratio of the compensation for regular workers to the compensation for contract workers. I find that, on average, the compensation for regular workers is 17% greater than that of contract workers in the first compensation group, while it is 24%, 45%, and 98% greater in the second, third, and final groups, respectively. This means that as regular workers' compensation increases relative to the prevailing minimum wage when moving from group 1 to group 4, contract workers' compensation remains close to the minimum wage in all groups. As mentioned in the data section, minimum wage enforcement is stricter for regular workers than it is for contract workers. Therefore, when regular workers are paid the minimum wage, their wages are likely to increase by a greater increment than contract workers' wages following a minimum wage hike. That is, regular workers will likely become more expensive, compared to contract workers, after the hike than they were before it. However, when the minimum wage increases and regular workers are paid well above it, but contract workers are paid close to the wage floor, there is more pressure on contract workers' wages. In other words, firms are more likely to substitute away from regular workers in the first compensation groups, but more likely to substitute contract workers for other inputs as we move in the latter compensation groups. These results, indeed, suggest a gradual change in which group of workers the firms replace. However, this pattern appears to take place at varying rates across firm types with routine intensive firms being the first to see a reversal, followed by firms in the average industry. This suggests that the minimum wage continues to bind for regular workers, even as non-wage compensation rises in non-routine firms. I find suggestive evidence that the minimum wage does affect a larger fraction of employees in non-routine industries. In Appendix C, I use NSS household survey data and regress the real daily wage data for employed individuals on the real minimum wage. I find that every rupee increase in the real minimum wage is associated with a real wage increase of 0.31 rupees for people employed in the average industry, and of 0.58 rupees for those employed in industries intensive in offshorable tasks. In comparison, the wage increases by 0.13 rupees for individuals employed in routine-intensive industries. This is also consistent with the stronger substitution patterns observed in non-routine firms within any compensation groups.

I present the event study results associated with the total effect of a typical minimum wage hike on the number of employees working on a typical workday in Figures I.1 to I.12 in Appendix I. The figures reveal several additional patterns. Firstly, they show little evidence of pre-event trend differentials, especially for firms in the first compensation group. Secondly, the substitution patterns described above happen gradually, and do persist in time for firms in this compensation group. In other words, a minimum wage hike appears to have a permanent effect on the employee mixes firms use. Gradual and persistent effects also seem to be present in firms of other compensation groups, but the results are estimated with less precision.

Together with the investment results, the substitution patterns between employee types are largely consistent with the model's predictions. Following a minimum wage increase, firms intensive in routine tasks substitute away from employees more likely to be bound by the minimum wage and towards all form of capital. Firms in the average industry see little change in capital investment, but substitute minimum wage workers for employees less likely to be affected by a minimum wage hike.[63] This labor-to-labor substitution is also observed in firms intensive in offshorable tasks who also see a decrease in capital investment. This is consistent with these firms offshoring certain tasks where labor and capital are used in tandem, and which are conducive to being done remotely. If these firms were asking workers to do offshorable tasks remotely from other Indian states where the minimum wage is lower, capital expenditure for the remote positions would still appear on firms' balance sheets. Therefore, we would be unlikely to see a fall in capital if this were the case. If firms were moving jobs to other parts of the country, we would also expect employment to increase in offshorable industries of a given state if wages rise in the same industries elsewhere in the country. I show in the aggregate section below that there is no evidence of that. I also show that minimum wages don't seem to have an impact on outsourcing for any groups of firms in Appendix L. The point estimate for the minimum wage is even negative (but remains insignificant) for firms in industries intensive in offshorable tasks, adding support to the idea that offshorable tasks are offshored rather than outsourced. However, to derive a more definitive answer

[63]If we are willing to make a series of simplifying assumptions about the model, it is possible to get estimates on certain elasticities. I find that the elasticity of substitution between Indian labor inputs is at least 1.24 and the elasticity of substitution between capital and workers is at least 2.4 in routine-intensive industries see Appendix N.

on offshoring patterns would require additional data on offshore inputs, which is not available, as far as I am aware.

5.3 Robustness

As mentioned in Sections 2 and 4, the results presented above are similar in sign and magnitude when using more conservative winsorizing cutoffs and when using an alternative border design identification strategy (see Appendixes E and F). The opaque decision process that states use in deciding minimum wages makes it hard to predict minimum wage hikes (Adhvaryu et al. (2021c)). Nevertheless, I show in Appendix G that the results are also similar when focusing on real minimum wage increases that exceed the national inflation level which may be harder to anticipate than lesser changes.[64] Given that minimum wages vary at the state, year, and industry level, it is possible that a worker in a given industry with a rising minimum wage also sees her outside option increase if the minimum wage also rises in other industries. In Appendix H, I include the average real minimum wage in other industries of the same state that have a statutory minimum wage and its interactions with the routineness and offshorability indexes and show that the estimates are virtually unchanged.

Before concluding, I explore whether layoff regulations affect how firms adjust to minimum wage hikes, and whether the hikes affect aggregate employment.

[64] For this exercise, I set the real minimum wage to its previous value, unless the change exceeds, or is equal to, the inflation.

5.4 Impact of layoff regulation intensity

In 1947, India adopted its Industrial Disputes Act which established layoff regulations for firms' regular and contract workers. The regulation established conditions under which workers could be laid off without consequences. In general, managers are not covered by layoff regulations and contract workers are employed on short-term contracts. Hence, firms can easily reduce the number of contract workers by not renewing their contracts. Therefore, the regulation applies primarily to regular workers. I follow Aghion et al. (2008) who builds on the work of Besley and Burgess (2004) to identify pro-employer, pro-worker, and neutral states that, respectively, facilitated, hindered, and did not change the difficulty of laying off regular workers, as dictated by the Act of 1947.[65] I run the same regressions for capital and employment separately comparing firms in pro-employer, neutral, and pro-worker states, and present the results in Appendix K.[66] I find that firms respond differently following a hike in the minimum wages depending on the layoff regulations' intensity. The exploratory results indicate that both the capital and the labor adjustments are stronger in pro-employer, and to some extent, in neutral states. This suggests that limiting the firms' ability to lay off workers also limits the speed at which they automate and offshore parts of their production following minimum wage hikes.

[65] Aghion et al. Identify 6 neutral states (Assam, Bihar, Haryana, Jammu and Kashmir, Punjab, and Uttar Pradesh), 6 pro-employer states (Andhra Pradesh, Karnataka, Kerala, Madhya Pradesh, Rajasthan and Tamil Nadu), and 4 pro-worker states (Gujurat, Maharashtra, Orissa, and West Bengal). The remaining unclassified states are excluded from this section.

[66] Fewer firms in Prowess are located in neutral states. For the capital investment regressions, I group pro-employer and neutral states together.

5.5 Aggregate employment

While the employment variables in the ASI data are useful in determining how firms switch between types of employees, it is important to note that they capture both intensive and extensive margin adjustments. Indeed, when the number of regular workers working during a usual workday falls for example, it is unclear whether some of these workers have been laid off, or whether some have experienced a reduction in work hours, or both.

From a policy standpoint, it is also important to know whether firms' adjustments affect aggregate employment. However, the minimum wages vary at the state and industry level, complicating any analysis of their effects on aggregate unemployment time series. Fortunately, the National Sample Survey presented in the data section includes data on the working individuals' employment status every five years or so. Therefore, I aggregate the number of workers employed by industry, district, and age quartiles for three waves of the NSS that overlap with my study period. In Table J.1 of Appendix J, I regress the log of the aggregate employment on the real minimum wages, and their interaction with the routineness and offshorability indexes. The point estimates are negative, but tiny in magnitude and insignificant when looking at all age groups together. This is consistent with the findings Menon and Rodgers (2017) and Soundararajan (2019). However, the results suggest a negative effect on employment for the younger group of workers (14-24 years old). For a typical minimum wage hike, employment tends to fall by 0.3% in the first age quartile across all firm types. If all industries were to experience a typical increase in their minimum wages, employment would fall by 140,000 for this age group at the national level. The results also indicate a fall in employment of 0.3% for individuals between 44-65 years old in routine-intensive industries following a typical minimum wage hike which is about 11,300 workers per industry at the national level. While firms are able to keep their profit margins stable, the results above suggest that some workers may suffer a welfare loss.

In Table J.2, I also control for the average minimum wage in the same industry and year, but in other states, and interact it with the routineness and offshorability indexes. All coefficients related to the average wage in other states are small and insignificant, suggesting that employment in an industry and state is not significantly affected by the minimum wages in the same industry elsewhere in the country. Hence, there is little evidence that firms in any type of industry move jobs in cheaper part of the country.

6 Conclusion

Minimum wage policies have been focal points in labor studies and policy debates alike for decades. The attention has been on the effect of these policies on aggregate employment. However, the conclusions reached have been mixed in both developed and emerging economies. Yet, little is known about the adjustment process for firms following minimum wage hikes. This may shed light on the mixed conclusions observed at the aggregate level. The structural transformation literature suggests that an increase in wages can push firms to upgrade their production to the best available technology and innovate, and therefore change, the production structure at the aggregate level. The automation and offshoring literature provides additional nuance and predicts that firms intensive in routine tasks are more likely to mechanize and automate their production, while firms relying on offshorable tasks are likely to relocate part, or all, of their operations to other countries.

In this essay, I explore how Indian firms that differ in their routine and offshorable task intensity adjust a wide array of capital and labor inputs following minimum wage hikes. I find that firms intensive in routine tasks invest more in machinery and computers, to the detriment of workers paid the minimum wage. This indicates that they automate certain tasks. Firms intensive in offshorable tasks rely less on Indian workers paid the minimum wage and computers, but more on other Indian employees. This suggests that some tasks combining workers and computers may be moved offshore, while other tasks are relegated to different employees in India. Firms that are not intensive in these two task types see little change in capital investment, but also replace workers paid the minimum wage with other employees. The adjustment done by firms allow them to keep their profit margin stable as the minimum wage rise in their industry.

Overall, these results indicate that firms' ability to automate and offshore certain tasks is a key driver of their heterogeneous responses to minimum wage hikes. The results indicate that while some tasks may be offshored and automated, there is also a substitution between different groups of employees. This may help us better understand why rising minimum wages may yield mixed results at the aggregate level. For example, some firms where the minimum wage binds stronger for regular workers substitute some of these workers with contractual workers. The opposite is observed in firms where the minimum wage is more likely to bind for contract workers. In addition, when workers' wages rise, some firms rely more on managers, while other firms rely less on them. At the national level, employees from all of these firms are clumped together. Hence, it is perhaps unsurprising that the literature has reported contradictory results, even within the same country. In the context at hand, I find evidence that employment at the national level falls for younger workers in all industry types, and for older workers in industries more intensive in routine tasks. Meanwhile, employment in the middle age group is unaffected.

Chapter II

Absenteeism, Productivity, and Relational Contracts Inside the Firm

7 Introduction

Relational contracts – informal agreements that leverage repeated interactions to overcome information or contractual specification and enforcement problems – are essential building blocks of the theory of the firm (MacLeod and Malcomson, 1989, Baker et al., 1994, 2001, Levin, 2003, Gibbons and Roberts, 2012, Chassang, 2010). Workplace collaboration among teams and across bosses and subordinates is the result of many non-contractible transactions that are disciplined by the promise of future rents or reciprocation. Yet, despite their fundamental importance, most of what we know about the form and function of relational contracts within the firm is anecdotal (Johnson et al., 2002, Board, 2011, Helper and Henderson, 2014, Gibbons and Henderson, 2012b,a). This is perhaps unsurprising, given that the numerous favors and promises among colleagues that make organizations run smoothly seem too ordinary to meticulously record. In contrast, the availability of detailed data on transactions *between* firms has spawned a rich literature on the causes and consequences of imperfect contract enforcement in firm-to-firm relationships (McMillan and Woodruff, 1999, Banerjee and Duflo, 2000, Macchiavello and Morjaria, 2015, 2017, Macchiavello and Miquel-Florensa, 2017, Cajal-Grossi et al., 2019, Khwaja et al., 2008, Hansman et al., 2017, Lafontaine and Slade, 2007, Atalay et al., 2019, Atkin and Khandelwal, 2019).

As a result of this scarcity of records of cooperation among coworkers within firms, many basic questions remain largely unanswered. For example, how prevalent are relational contracts among coworkers? What specific frictions do they help overcome? How well do they work – that is, how close are outcomes to first-best? What barriers prevent relationships from forming or maturing, and do these barriers lead to sub-optimal quantity and quality of relationships? Our study aims to fill this knowledge gap. We shed light on these questions using unique data on relationships among managers in a large ready-made garment firm in India. Workers in this firm are organized into production lines, and each line is typically led by one manager. Managers play a key role in determining line productivity in this setting (Adhvaryu et al., 2021d,a, Boudreau, 2020, Macchiavello et al., 2020). They assign sewing machine operators to tasks; deal with bottlenecks in throughput along the line; and monitor and motivate workers to meet production targets (Adhvaryu et al., 2021b).

We focus on one key challenge managers face in this setting – high and often unpredictable worker absenteeism. This challenge is common across organizations in many contexts, particularly so in low-income countries (Chaudhury et al., 2006, Banerjee and Duflo, 2006, Kremer et al., 2005, Duflo et al., 2012). In our sample, for example, the average daily worker absenteeism rate is eleven percent, and for any given production line, the rate is at least twenty percent once in every ten days. We show, via fixed effects as well as instrumental variables specifications, that these fluctuations do indeed have substantial impacts on line productivity, implying that absenteeism is of first-order importance both to managers and to the firm.

How do managers smooth production in the face of this uncertainty? We demonstrate that managers rely on relationships through which they "lend" and "borrow" workers based on absenteeism shocks realized at the start of each production day. The lack of an internal labor market in this setting is likely due to information frictions both within and across levels of the managerial hierarchy. Among line managers, the basic information problem is related to the observability of "need." In the few hurried minutes before production begins each day, it is infeasible to verify worker shortages on any particular production line; trade in a spot market would likely break down. Similarly, across managers and their higher-ups, truthfully reporting shortages, optimally reallocating workers, and communicating these changes across the factory workforce is likely to come up against time and span of control constraints. Managers in this setting are also able to identify "unobservable" comparative advantages in particular tasks for their own team's workers (Adhvaryu et al., 2021b); these differences among otherwise similar workers are not readily evident to managers of other lines, which compounds the asymmetric information problem just described. These frictions create potential value in relationships among managers. As one manager aptly conveyed to us, "...we share workers with an understanding that we might need to borrow workers in the future." To study this behavior, we exploit unique administrative data on daily worker absenteeism, line productivity, and, importantly, transfers of workers across managers.

We begin by showing that daily fluctuations in absenteeism are not highly correlated across managers, even for managers working on the same factory floor. This, paired with the concavity of the production function with respect to number of workers, creates potential value to "borrowing" workers with the promise of repaying that debt in the future. In particular, a manager whose production line would fall behind due to high worker absenteeism could borrow from a colleague whose line happened to have incurred a less severe shock that day, presumably with the promise of repaying the favor should the relative states be switched in some future period. We also check that absenteeism is balanced across managers of differing quality or average efficiency and provide evidence that line-day absenteeism is plausibly exogenous in this setting.

We find that while managers do indeed exchange workers in this manner, many potentially beneficial transfers are left unrealized. Most managers have active relationships (i.e., are engaging in regular lending or borrowing of workers) with only two or three colleagues, out of on average more than twenty potential relationships with other managers working in their factories. The average manager forgoes 15-19 partnerships. As a result, for relatively large worker absenteeism shocks, which have the potential to generate substantial productivity losses, we show that managers struggle to leverage relationships to make up for the shortfall in workers.

To further study the nature of lending and borrowing behavior among managers, we present a simple model of relational contracting, in which two managers decide whether and how much to trade with each other.[67] The model, which features stochastic absenteeism states, fixed costs of trading, and learning about partners' (privately known) types, generates a unique symmetric stationary relational contract that characterizes managers' interactions. Additional predictions can be made for interactions along the transition to this steady state, as managers learn about each other's type.

We test the model's predictions using a dyadic data set of managers within

[67]Most of the seminal models of relational contracts involve a transfer of utility between risk neutral agents; while in our setting managers transfer workers who are inputs in a concave production function. Accordingly, we propose a novel simple framework that better represents the context at hand, drawing elements and intuition from many of the established models of relational contracting.

factories. Worker-by-day data on absenteeism, combined with a precise mapping of workers to lines for every production day, enables us to track transfers of workers across all manager dyads. In line with the model's predictions, we find that borrowing is indeed affected by absenteeism realizations, the maturity of relationships, and transaction costs. One important takeaway from this analysis is that both physical distance *and* "identity-based" distance such as gender, education, age and experience differences between the managers matter for the intensity of transfers in relationships.[68]

We then discuss several additional results and demonstrate the robustness of our main results in several ways. First, we show that the trading patterns predicted by the model are reflected on the extensive margin of any trading between patterns in addition to the intensive margin of quantity of workers traded shown in the main results. Then, we document that managers are more selective of the partners with whom they trade their higher productivity workers, as would be predicted by a generalized version of the model in which worker quality varies. We also use the factors of managerial quality identified as most important for productivity in Adhvaryu et al. (2021d) to investigate which types of managers appear to trade most actively. We find that managers exhibiting greater Control (i.e., a stronger belief in their own ability to impact performance rather than acquiescing to fate or chance) are more active traders; while managers exhibiting greater Attention are less active traders, consistent with a greater ability to leverage within line worker-task reassignments to

[68]That is, not only is it the case that physical distance on the factory floor determines the intensity of trade, but what also matters for these contracting outcomes is the similarity of managers in terms of identity characteristics. This is an important fact because while both types of distance relate to transaction costs, physical distance might also reflect inherent features of the organization of production on factory floors that may make trading more likely for purely technical reasons. Demonstrating that a "softer" distance based on managerial characteristics matters in addition to this provides more robust evidence in support of the predictions of the model of relational contracts set out in the essay.

mitigate any potential productivity losses (i.e., to "make do" with the available workers on the line) as shown by Adhvaryu et al. (2021b) in a similar setting.

Finally, Adhvaryu et al. (2021a) provide evidence in a nearly identical setting that upper managers sometimes systematically reorganize workers across lines for many days, shifting high efficiency workers from high productivity lines to low productivity lines at the beginning of an order to preemptively ensure that deadlines for important buyers are met. Accordingly, we check that these worker moves across lines are distinct from the short term sharing of workers in response to idiosyncratic absenteeism shocks we aim to study here, which is balanced across high and low efficiency workers and lines and occurs throughout the duration of the order. We then demonstrate that our results are robust to excluding worker moves most likely to reflect this systematic reorganization of workers across lines (i.e., moves initiated within the first week of an order and moves lasting too many days to likely be responses to absenteeism).

Finally, we perform several counterfactual simulations to assess the extent to which relationships among managers matter for aggregate (plant-level) productivity. In particular, first we assess what would happen if managers did not share workers at all – i.e., in a world in which there were no relational contracts. We find that aggregate productivity in this world would be roughly 0.9 percent lower than the *status quo* (relational contracting) equilibrium. Next, motivated by the fact that there seem to be very few active relationships per manager, we ask what the gains to increasing the number of trades would be.[69] We trace out a concave function that shows that productivity would increase

[69] We note that some opportunity or effort cost likely exists such that managers are not leveraging valuable trading partnerships in the status quo equilibrium, and therefore conceptualize this thought experiment as the introduction of some cost reducing technology such as an app or messaging network that allows for managers to trade workers without having to spend time and effort to meet with each other.

substantially (by up to 1.6 percent) if the costs of relationship formation decreased. That is, the value of additional relationships to the firm in this context is quite substantial. Such an increase in efficiency would translate roughly to a 1.44 million US dollars increase in annual profit for the firm. Benchmarking these gains to the (simulated) gains from a reduction in absenteeism, we find that maximizing the number of relationships would achieve up to 98% of the productivity gained from a 50% reduction in absenteeism, suggesting that the costs of misallocation of labor *within* the firm can be as important as the costs of market failures (such as those that lead to worker absenteeism) outside the firm's direct control.

Our essay makes three main contributions. First, much of the rich theoretical basis of organizational economics rests on the idea that repeated interactions among coworkers and between managers and employees create value in settings with incomplete contracting (MacLeod and Malcomson, 1989, Baker et al., 1994, 2001, 2002, Levin, 2003, Gibbons and Roberts, 2012, Chassang, 2010). Yet, despite growing empirical evidence on relational contracts *across* firms, which often benefits from detailed transactions data across buyer-supplier relationships (McMillan and Woodruff, 1999, Banerjee and Duflo, 2000, Macchiavello and Morjaria, 2015, 2017, Macchiavello and Miquel-Florensa, 2017, Cajal-Grossi et al., 2019, Atkin and Khandelwal, 2019), the empirical support for theories within firms is less complete. Specifically, informal agreements between employees within a firm, like those studied here, likely abound both across and within levels of the organizational hierarchy. While a recent body of evidence has documented informal agreements across levels of the hierarchical structure such as subjective performance bonuses between employers and employees (see Lazear and Oyer (2013), Gil and Zanarone (2017) for reviews), little empirical work to our knowledge exists on informal agreements formed between employees within the same level of the organizational hierarchy.[70] We provide direct empirical characterization of this latter type of agreements by studying relational contracts taking place between peer managers supervising parallel production teams. We produce new evidence that the barriers to relationship formation and maturity are non-trivial, and also that encouraging new relationships by reducing these barriers can result in substantial positive gains for both managers and the firm.

Second, we contribute to the literature in personnel economics that has documented how co-workers impact each other's productivities (Amodio and Martinez-Carrasco, 2018, Bandiera et al., 2013, 2010), as well as how the interaction between workers and their supervisors determines firm productivity (Lazear et al., 2015, Frederiksen et al., 2017, Adhvaryu et al., 2021d, Hoffman and Tadelis, 2018). Our study adds to this literature evidence on how managers can impact the productivity of each other's teams by way of cooperative resource sharing. Our results also add to the large body of empirical evidence on the impacts of management on productivity (Bloom and Van Reenen, 2007, 2011, McKenzie and Woodruff, 2016, Gosnell et al., 2019, Bloom et al., 2016), documenting that one way in which managers contribute to the productivity of their teams is to enable smoothing of resource shocks by way of cooperation with fellow managers.[71]

Finally, we contribute to the understanding of the allocation of talent within firms. The assignment of workers to teams and tasks is a key feature

[70] While Sandvik et al. (2020) do not study existing relational contracts, they devise an experiment in which salespersons are paired to share sales information and tips. In essence, they experimentally form relational interactions between workers and find that sales can improve by as much as 15%.

[71] Middle managers like the production line supervisors we study are often emphasized as enablers or constrainers of worker productivity (Adhvaryu et al., 2021d, Levitt et al., 2013), particularly in low income countries and labor-intensive manufacturing settings (Bloom and Van Reenen, 2007, McKenzie and Woodruff, 2016, Boudreau, 2020).

of the organization of production within firms, both in theory (Lazear and Oyer, 2007, Lazear and Shaw, 2007, Holmstrom and Tirole, 1989, Kremer, 1993, Gibbons and Waldman, 2004) and in practice (Adhvaryu et al., 2021b,a, Amodio and Martinez-Carrasco, 2018, Amodio and Di Maio, 2017, Bandiera et al., 2007, 2009, Hjort, 2014, Friebel et al., 2017, Burgess et al., 2010, Bloom et al., 2010b). We add to these studies by demonstrating that the allocation of workers to teams is governed in part by relational contracts among managers, and that the internal misallocation of labor can be quite costly.

8 Context

8.1 Industry context

We study production line managers at Shahi Exports, Pvt. Ltd., the largest readymade garment manufacturer in India and among the top five largest such firms in the world.[72] As a labor-intensive manufacturing industry that has characterized the initial stages of industrialization in many parts of the world, but one that today utilizes modern production concepts such as specialization, assembly lines, and lean production, garment manufacturing provides an excellent setting to study the impacts of personnel management practices on productivity.

Shahi Exports is a contract manufacturer for international brands. Orders from brands are allocated by the marketing department of each production division (Knits, Mens, and Ladies) to factories based on capacity and regulatory and/or compliance clearance (i.e., whether a particular factory has been

[72] India is the fourth largest exporter of garments in the world (WTO, 2018).

approved for production for that brand given its corporate and governmental standards). Within the factory, the order will then be assigned to a production line by first availability.[73] The order will then be produced in its entirety by that production line and prepared for shipment in advance of the contracted delivery date.

8.2 Production process

There are three main stages in the production process. First, fabric is cut into subsegments for different parts of the garment, organized according to groups of operations for each segment of the garment (e.g., sleeve, front placket, collar), and grouped into bundles representing some number of garments (e.g., materials for 20 sleeves or 10 collars). These bundles of materials are then fed into the sewing line at several feeding points according to which segment of the line is producing each segment of the garment. The operations to construct each portion of the garment and ultimately attach these portions together to make complete garments makeup the sewing part of the production process. Finally, the sewn garments go through finishing (e.g., washing, trimming, final quality checking) and packing for shipment in the final stage of the process.

In our study, we focus on the sewing process as this step makes up the majority of the production timeline, utilizes the majority of the labor involved in production, and lends itself to detailed observation of team composition and output as needed for our analysis. In this essay, we leverage production data from 4 factories consisting of a total of 73 sewing production lines. We focus the analysis on the spans of consecutive months where the production of most

[73] That is, whichever line happens to be finishing its current order when an incoming order is processed will be allocated that new order.

lines is recorded consistently for each factory. As a result, our sample consists of 6-7 consecutive months per factory.[74]

A typical sewing line has 50-60 permanently assigned workers. Each line works on one order at a time, for roughly 3-4 weeks on average, until the order is complete. The sewing process is split into individual machine operations, with each operation typically being completed by one worker assigned to a single machine. In practice, production may deviate from this structure if, for example, several machines and workers are charged with a particular operation which has proven to be slower than expected, or if an extra worker is staffed alongside a machine operator to help with supporting tasks (e.g., pre-aligning pieces of fabric or folding and ironing seams prior to stitching).

Operations are organized in sequence, grouped by segments of the garment, with groups punctuated by feeding points at which bundles of materials for a certain number of segments (e.g., 20 shirt fronts with pockets) are fed. For example, a group of 5 workers assigned to 5 machines will complete 5 operations (sometimes the same operation) to produce left sleeves, another group will do the same for right sleeves, another for shirt fronts with pockets, and another group will work on the collar. Bundles of completed sections of garments will exit segments of the line and be fed into other segments of the line charged with attaching these portions of the garment together until a completed garment results at the end of the line.

[74] Unit 1: September 2013-February 2014, Unit 8: November 2013-April 2014, Unit 23: August 2013-February 2014, Unit 28: August 2013-February 2014 (all dates are inclusive). While the dates do not fully overlap across units, no trades take place across units such that any non-overlap is not an issue for the analysis. Note that we drop lines that are open only temporarily in cases of excessive demand and lines for which the production data was not recorded consistently over the periods listed above. The workers from these sporadic lines are not counted as workers borrowed on the lines retained in our sample.

8.3 The role of managers

Each production line has a manager (and sometimes several assistant managers, often serving also as feeders). Managers are paid a fixed salary and are eligible to receive a linear productivity bonus above a certain order-specific efficiency threshold. Each manager is assigned permanently to his line and is responsible for several key oversight tasks. First, when a new order is assigned to a line, the line manager must determine how to organize the production process. This decision depends crucially on both the machines and workers available and the complexity of the style of garment to be produced.

Importantly, this initial line architecture (known as "batch setting") is time consuming and costly to adjust in the middle of producing an order. It is always set at the start of a new order and is rarely and minimally changed for the life of that order to avoid downtime. If productivity imbalances or bottlenecks arise, managers will most often switch the task allocations of some set of workers across machines, or add a helper or second machine to some critical operations, preserving the line architecture otherwise (Adhvaryu et al., 2021b). This recalibration of the worker-machine match (known as "line balancing"), along with some machine-specific technical calibration, is most likely responsible for the marked increases in productivity seen over the life of an order in this setting (Adhvaryu et al., 2021d).

8.4 Absenteeism

On a typical day, 10-11% of workers are absent. Nearly all absenteeism is "unauthorized" – i.e., it is not reported formally to the firm before the date of absence. While the determinants of absenteeism are likely many (and workers are not always forthcoming about reasons why they were absent), anecdotally, common causes include health shocks to the worker or her family members; religious or cultural festivals that require travel to workers' native places, which are often villages in rural areas across India; and temporary economic opportunities that workers perceive as more lucrative than the wages lost due to absenteeism (e.g., harvesting coffee or areca nuts). A loss in wages is the main consequence for workers of taking unauthorized leave; workers are almost never fired given that Indian labor law mandates very high firing costs, particularly for large firms (Adhvaryu et al., 2013).[75]

As we present in section 9.3, lines are on average equally subject to absenteeism. Absenteeism shocks are frequent and large, and can have a substantial negative impact on line productivity. Worker absenteeism creates potential bottlenecks in throughput, if one or more segments on the production line operate more slowly than usual due to lower manpower. The fewer the workers within a given segment, the smaller the "buffer stock" between segments likely is, and thus the higher the probability that one segment must wait for a previous segment's inputs to continue producing.

Managers compensate for manpower shortages in part by reconfiguring worker-operation matches within the line to ease bottlenecks, and in part by asking other lines for workers, as we describe in detail below. The shape this *ex post* recalibration takes, and the resulting need for additional workers, are best assessed by the line manager himself, as he is most knowledgeable of the style of garment currently being produced and of the comparative advantage

[75]We use payroll data to find whether the workers leave the firm at any point between 2013 and 2015, inclusive. We regress the probability of leaving the firm on the number of days the workers were absent during the study period. The regression coefficient is very small and insignificant (β = 0.00014, SE=0.00009). 64% of workers eventually separate from the firm. The regression coefficient implies that if a worker were to be absent for a whole month during the 6-month study sample they would have a 0.65% higher probability of separating with the firm in the future, which is extremely small.

of his available workers at the tasks necessary for that order (Adhvaryu et al., 2021b). These differences among otherwise similar workers are not readily evident to managers of other lines. It is infeasible given time and information constraints that managers are able to accurately assess manpower needs of lines other than their own. The complexity of the initial batch setting and the dynamic nature of line balancing thus gives rise to asymmetry of information across managers of different lines as well as limitations to the ability of higher level managers (such as floor in-charges and factory general managers) to solve the resultant reallocation problems.[76]

8.5 Allocation of Workers Across Lines

Absenteeism is a key driver of worker movements across lines. Figure S.1 plots the distribution of absenteeism and the distribution of borrowing spells. The figure shows that the two closely match providing suggestive evidence that the two phenomena are connected. However, systematic reorganization of workers across lines to reduce the likelihood of missed deadlines for important buyers is another important source of movements of workers across lines.

Adhvaryu et al. (2021a) show that this systematic reorganization preemptively takes place at the beginning of an order. These moves often span for the whole first week of the order (6 workdays) as shown in Figure S.2 and are orchestrated by upper management. When upper management is confident that the order deadline will be met, workers are often returned to their original lines. This systematic reorganization of workers across lines to prevent

[76] This asymmetry is made more difficult to resolve given the short amount of time that the managers have at the beginning of the day to start production. Most workers arrive just before 9 in the morning and production is expected to start promptly at 9 am. Within those few minutes, managers must guess whether the missing workers are really absent or whether they will show up late. Given this, they need to decide whether they should try to borrow workers from other lines.

missed deadlines also typically involves high quality workers from high quality lines being moved to lower quality managers leading to a Negative Assortative Matching (NAM) between workers and managers.

We show that this NAM pattern is not driven by the short term trading spells in response to idiosyncratic absenteeism shocks we study here. That is, we focus on the short-term absenteeism-driven trades which can take place at any point during an order. We document below that these trades are much more consistent with relational contracting than they are with central planning. In Appendix S, Figure S.3 shows that short-term trades flow between managers of a similar quality level and do not depend on worker quality confirming that these trades are distinct from the systematic reorganization of workers across lines to avoid missed deadlines for important buyers studied in Adhvaryu et al. (2021a).[77] We also show in Figure S.4 that managers form long-term partnerships with managers of similar quality levels.[78] Finally, we demonstrate in Tables S.1 and S.2 that our results are robust to excluding all worker moves which are likely to be centrally coordinated (i.e., trades taking place during the first week of an order and trade spells too long to likely be responses to idiosyncratic absenteeism shocks).

[77]In Figure S.3, we first obtain manager and worker fixed effects from the same AKM specification used in Figure U.3 and then split the sample of managers at the median within unit and floor and split the workers at the median within unit. This ensures that there are high and low quality workers and managers on each floor. We count the number of high and low efficiency workers traded from high efficiency lines to high efficiency lines, from low efficiency lines to low efficiency lines, and from high (low) efficiency lines to low (high) efficiency line. We plot these numbers when excluding trades going to borrowing lines in the first week of an order in the left panel, and when excluding long trades (longer than 5 days) in the right panel.

[78]In Figure S.4 we obtain the same manager effects used in Figure S.3 and split again at the median within unit and floor such that there are high and low quality managers in each unit-floor. We look at every manager's first, second, and third most frequent partners and count how many matches are between managers of similar and different quality level. Managers are of similar efficiency levels if they both are high efficiency managers or both low efficiency mangers. They are different otherwise.

8.6 Cooperation between managers

In practice, when facing larger absenteeism shocks that can be mitigated via line reconfiguration alone, managers often ask to borrow workers from fellow managers' lines. Managers "lend" workers knowing that they also face the prospect of absenteeism shocks in the future, and expecting that the favor of lending workers will be returned at that time. Interviews with managers in the factories under study regarding strategies for addressing absenteeism were quite revealing. One manager reported that "when facing absenteeism, I will try to get workers from other managers by talking to them directly." Another said that "managers form relationships mainly through being on the same floor and understanding that cooperation is mutually beneficial." This *quid pro quo* in essence defines the relational contract we empirically study in this essay.

It is worthwhile noting that this cooperation is likely very difficult to organize or impose at higher levels of management, and impossible to formally contract on via existing organizational structures, due to the private information each manager has about their own worker requirements given the style, workers present, and possible recalibrations of worker-operation matches, for any given set of realizations of absenteeism shocks across lines. This means that line managers rely on their relationships as the primary safeguard against the deleterious effects of absenteeism on productivity. Moreover, cooperating can entail a contemporaneous loss for the lenders. Indeed, managers receive a base wage and are entitled to bonus pay if they produce above a certain daily threshold. There are no direct monetary incentives for lending workers. Hence, by lending workers managers may realize this bonus with lower probability in the current period. This pay structure is not inherently designed to foster cooperation and may indeed discourage lending. However, managers may still benefit from trading in the long run. We show in subsection 9.6 that trading is highly symmetric in that managers repay the workers they borrow by lending back to their partners. This suggests that managers are willing to lend despite the implicit (contemporaneous) disincentives created by the pay structure. Such systematic and symmetric repayment of borrowed workers would be inconsistent with centralized planning of worker moves.[79]

9 Data and Empirical Facts

To start our investigation into relational contracting, we document the daily flows of workers between pairs of line managers. In this section, we describe the data we use and report empirical facts depicting the importance of absenteeism and the nature of cooperation among managers. The data shows that absenteeism shocks are large, frequent, and idiosyncratic. Managers appear able to deal effectively with absenteeism up to roughly 9%; past this point, overall efficiency begins to suffer. Managers borrow workers from other lines to cover for their own missing workers, but this cooperation appears somewhat limited. Managers do not trade with all possible partners, such that many productivity enhancing trades go unrealized.

9.1 Key variables

For each production day, we observe the identifier of each worker and their average hourly productivity on the line to which they were assigned for the

[79] In Appendix O, we also show that whether managers are on the same factory floor and the physical distance between them if on the same floor are uncorrelated with their demographic similarity, indicating that upper management does not appear to be placing demographically similar managers nearer to each other in an effort to foster trading relationships.

day. Each line has a permanently assigned manager as well as a set of workers assigned by default to that line. Each worker's default assignment, or "home line," is easily determined in the data as the line on which the worker spends the vast majority of their time. The data show that workers spend on average more than 90% of their days on one primary line over a given 3 month period, for example.[80]

In response to absenteeism of home line workers on a given day, line managers can borrow workers from other lines and/or lend some of their own home line workers to other lines. We know whether each worker is absent on a given day by whether their productivity is recorded at all, irrespective of the line on which they appear to be working. Accordingly, we define the percentage of absenteeism as the number of the home line workers of a line that did not have any recorded productivity on a given day divided by the number of home line workers usually available to that line. For example, if a line has 50 home line workers and 5 are not working on any line in the factory on a given day, then we calculate the absenteeism of that line as $5/50 = 10\%$.[81] Lines can differ in size across units, mainly driven by the configuration of the factory floor and the types of garments the factory makes. As a result, one missing worker may not affect all the lines the same way; while 1% of workers absent is more likely to reflect a similar magnitude of shock. For this reason, the percentage of available workers absent is our preferred measure and allows us to pool the results easily in figures and regression analyses.

We are also able to identify which workers were borrowed from another line. That is, if a worker has recorded productivity for a given day on a line

[80] We provide more detail on the determination of workers' home line in Appendix W.

[81] We allow the pool of available home line workers to change over time, to reflect both more permanent reassignments to new home lines as well as worker attrition from the factory. To account for turnover, we assume that workers who did not show up for two consecutive weeks or more are no longer part of a manager's pool of available home line workers.

other than their current home line, we know that the manager of that line has borrowed them from their home line manager for the day.[82] With these measures of absenteeism and borrowing and lending of workers in hand, we construct our main dyadic dataset by pairing each production line to their potential partner lines.[83] In addition to the absenteeism of each line in the pair, we are interested in the impacts of physical distance between lines and the maturity of relationships between managers of two different lines on whether and how many workers are exchanged. We measure relationship maturity by the cumulative number of days two lines have exchanged workers up to the observation date.[84] Distance is measured in feet between two production lines on the same floor.[85]

In addition to physical distance, we also look at the effect of the demographic (dis)similarity between pairs of managers (via gender or education differences, for example). In Table O.3, we present the demographic composition of the managers in our sample. For each demographic variable we show the most common category across managers in the sample.[86] Most managers are male and Kannada-speaking. Most identify as Hindu with roughly 40% belonging to the "general" caste category. More than 40% have at least passed the 10^{th} grade and more than two-thirds were born in the state of Karnataka,

[82]Note the productivity of all workers is reported regardless of the task they do.

[83]In other words, if manager i has 10 potential partners, the first row lists the number of workers borrowed by line i from the first partner, the second row lists the number of workers line i borrows from the second partner, and so on until the 10th partner. We define the set of potential partners for a given line as every other line on the production floor. There is no explicit policy stopping managers from borrowing workers across floors in units that have multiple floors. However, in practice trade across floors rarely occurs.

[84]We explore cumulative number of workers traded between two lines to date as an alternate measure, and find no meaningful differences in results.

[85]We do not have a measure of distance for lines on different floors, but given the extreme rarity of trades across floors we ignore these trades in our analysis.

[86]The manager identities and demographic data is obtained from a one-time survey of the managers. Accordingly, we cannot observe managers moving across lines over the study period, but were told by the firm that such moves are extremely rare if they happen at all, especially over a short period like the 6-7 month spans we study.

but outside the Bengaluru metro area.

In Table 10, we present summary statistics of key variables at the line level. Lines typically have 56 home line workers. On average 10.9% of home line workers are absent on any given day corresponding to 5 to 6 workers absent. On the factory floor, lines either run parallel or end-to-end or both. Factories have typically 17-18 lines (mean 17.5, SD 3.42) spread across 3-4 floors (mean 3.75, SD 1.71) with roughly 5-6 lines on each floor (mean 5.23, SD 1.82). Lines are on average 9 to 10 feet from their potential partners on the factory floor.

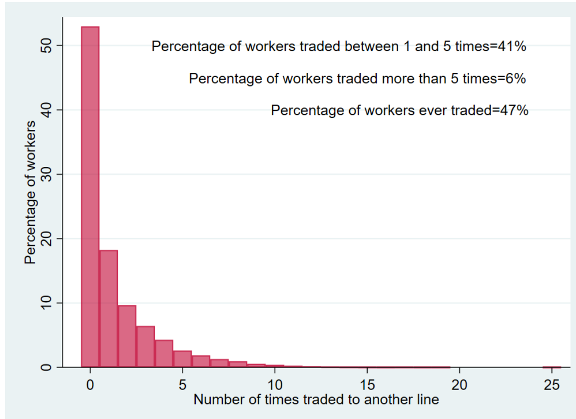
In Figure 7, we show the frequency of trades of the workers in our sample. Over the span of the data, approximately half of the workers are traded to other lines, and a large fraction of them are traded multiple times.

Table 10: Summary statistics at the line level

Variables	Mean/(S.D.)
Number of home-line workers (absent or not)	56.27 (16.49)
Number of workers present on the line (home-line or not)	50.80 (18.89)
Number of home-line workers present in the unit	50.80 (16.69)
Percentage of home-line workers present in the unit	89.09% (12.92)
Number of home-line workers absent	5.74 (7.02)
Percentage of home-line workers absent	10.90% (12.92)
Distance in feet from other lines	9.37 (5.88)
Number of line by day observations	13,524

Note: The data includes daily worker-level data from 4 garment factories spanning 6-7 months for each factory. Our sample consists of 73 sewing production lines. A typical production line has between 50-60 workers which usually corresponds to one worker per machine. Each production line has a line manager (and possibly 1 to 2 assistant managers, often serving also as feeders). Absenteeism is defined as the difference between the number of home line workers present in the factory on a given day and the total number of home line workers available. Distance is measured in feet between two production lines on the same floor.

Figure 7: Frequency of trades by workers



Note: We compute the number of times a given worker is traded to another line and plot the distribution. We count only new trades. Hence, if a worker is traded for 2 consecutive days to the same line, we do not count the 2 days as 2 separate trades.

9.2 Absenteeism and line productivity

We begin our presentation of empirical facts by documenting the relationship between absenteeism and productivity at the line day level. In the garment industry, efficiency is the global standard to measure productivity. The target quantity of a specific garment to be produced is determined from a measure of garment complexity called the standard allowable minute, or SAM. SAM is the number of minutes it should take, in an optimal setting, to produce one unit of a certain style of garment (e.g., one men's shirt).[87]

[87]SAM is a standard measure used in the garment industry that is drawn from a database of industrial engineering standards that documents the estimated time each operation should take and the operations that are estimated to be required to produce one unit of a garment of a certain style. In reality, workers on a line producing a men's shirt do not produce one shirt at a time, but produce buffer stocks of certain parts of that shirt (sleeves, collars, torsos,...), which are then assembled by separate workers. In addition, workers may be absent, their productivity may decrease from one hour to the next, machines may break, etc. Hence, the number of operations needed and the time needed for each operation may differ from what the SAM measure would suggest.

For example, it should take 30 minutes to produce one style of men's shirt if it has a SAM of 30. If the production of this shirt is split into 60 operations, the average SAM per operation would be 0.5 (i.e., each operation should take 30 seconds to complete on average), with SAM for each specific operation adjusted to reflect the complexity of the operation. Workers doing a specific operation with SAM of .5 should complete $60/0.5 = 120$ operations per hour.[88] The efficiency of a worker (per hour) is simply the number of operations she is able to perform per hour divided by the target number of operations per hour given by the SAM. If a worker is producing left sleeves and has a target of 120 sleeves per hour under the SAM, but produces 60 sleeves per hour on average in the course of a day, then her efficiency is 50% for that day.

To calculate daily efficiency of a line, we simply average the efficiency of the workers working on this line that day. In our data, the average hourly efficiency at the line level is 49.09% (SD 15.85%). Realized efficiency is far from 100% because the SAM reflects production in an optimal environment. Indeed, the SAM measure does not account for the fact that workers may become less productive as the hours go by or that machines may break and that bottlenecks may arise.

Figure 8, panel (a), plots line average efficiency against the percentage of home line workers absent, showing a decreasing and concave relationship. That is, absenteeism has little effect up to 9 or 10%, but has a large negative effect on efficiency thereafter. Average efficiency drops from above 50% at less than 10% absenteeism to below 45% at 20% absenteeism. Note that this panel plots the relation between absenteeism and efficiency after any realized trades. We might want to see this relationship before any trading occurs, but

[88] If another operation takes longer than average and has a SAM of 1 for example, then workers doing this operation are expected to do $60/1 = 60$ operations per hour.

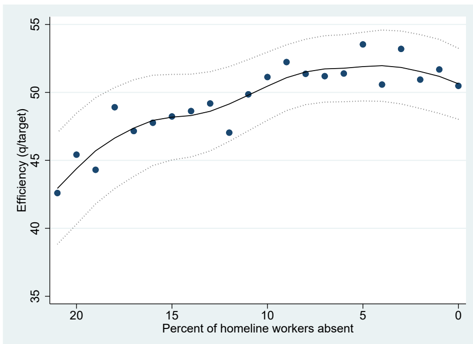
restricting the sample based on high or low realized trading would of course conflate any inability to borrow with unobservable true need for borrowing.

Figure 8, panel (b), on the other hand, plots the average efficiency of the line against the number of workers present on the line that day (whether or not this line is their home line, i.e., including realized trades) as a percentage of the number of home line workers assigned to this line. We can see that when a line has approximately 93% or more of its designated number of workers, efficiency remains relatively constant at around 52%.

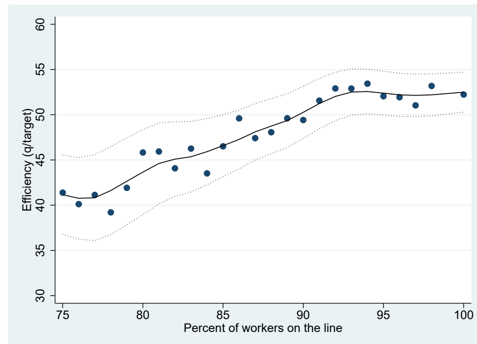
Taken together, the figures show that large absenteeism shocks appear to be detrimental to line productivity, but that fairly small shocks have little impact. This could reflect both the shape of the production technology as well as manager ability to make do with the available workers (i.e., set the batch at the start of the order to accommodate future absenteeism shocks and perform worker-task reassignments to mitigate potential losses due to absenteeism shocks). In either case, the figures show that an average line experiencing little to no absenteeism on a particular day (e.g., more than 93% workers present) may actually be able to spare some workers without forfeiting productivity; while a line experiencing a large absenteeism shock (e.g., less than 90% workers present) could benefit greatly from being lent those spare workers.

Figure 8: Average line-level efficiency...

(a) ...per percentage of "home line" workers absent



(b) ...per percentage of workers present on the line



Note: In the first panel, we compute the average efficiency of the workers on the line by percentages of absenteeism. Scatter depicts the mean within integer bins of absenteeism; solid line depicts a nonparametric fit; and dotted lines represent the 95% confidence interval. We restrict focus to days in which lines have 25% absenteeism or less as larger absenteeism is rare. In the second panel, we plot the average efficiency of the line against the percentage of workers working on the line. Percentage of workers on the line is calculated relative to the number of home line workers assigned to this line. We ignore rare cases when less than 75% or greater than 100% of the number of assigned homeline workers are present. Scatter depicts the mean within integer bins of absenteeism; solid line depicts a nonparametric fit; and dotted lines represent the 95% confidence interval.

9.3 Absenteeism shocks are large, frequent, and idiosyncratic

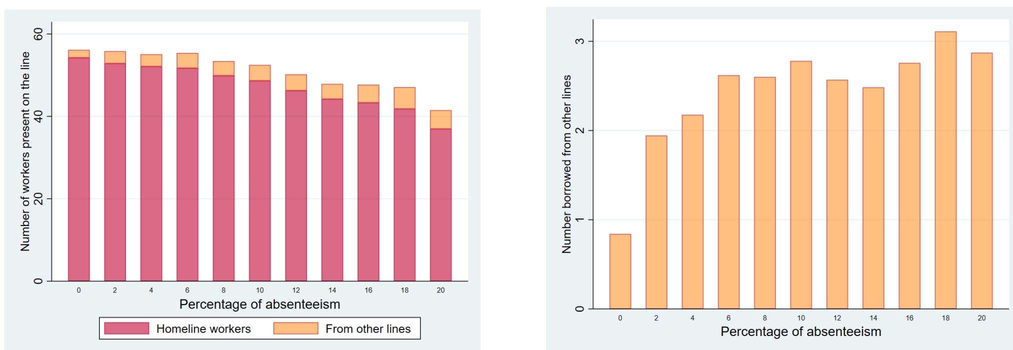
The potential for gains from trade of workers between lines with high and low absenteeism on a given day depends crucially on how frequently lines experience absenteeism shocks large enough to impact productivity and how likely it is that some other line on the floor is experiencing much less absenteeism on the same day. To investigate this, we count the percentage of lines in the sample that experience an absenteeism of at least 10% for each day of production and we plot the density across days. We do the same for shocks of at least 15%, 20%, and 25% and plot each density in Figure P.1. The figure clearly shows that large shocks are quite frequent. On any given day, roughly 35% of lines on average experience an absenteeism shock of at least 10%; roughly 17% of lines (or more than 1 line on a floor containing 6 lines) experience a shock of at least 15%; 9% of lines experience a shock of at least 20%; and 6% (or 1 line in a factory with 16 lines) experience a shock of at least 25% (or nearly 14 out of 55 home line workers absent).

In Table P.1, we report the average within day correlation in absenteeism of different lines across units, within units, and within floors. While the correlation increases slightly across specifications, the magnitudes all remain small. The within floor-day correlation, most relevant for determining opportunities for trade among line managers, is only 0.145. This confirms that, since absenteeism shocks are largely uncorrelated even for lines on the same floor, managers could potentially mitigate the burden of absenteeism by borrowing workers from lines experiencing less absenteeism on a given day.

9.4 Managers borrow workers to mitigate the impact of absenteeism

Figure 9: The number of workers borrowed...

(a) ... increases with absenteeism (b) ... increases up to a certain point



Note: In the first panel, The full bars represent the average number of workers on the line for different percentages of absenteeism across the lines in our sample. The darker bars indicate the average number of home line workers on the line and the paler bars represent average number of workers borrowed. In the second panel, we show the average number of workers borrowed across lines by percentage of absenteeism. The bars here are the same as the paler bars in the first panel.

Figure 8, panel (a), indicates that managers should want to borrow more workers as their absenteeism increases, and Table P.1 suggests that some other lines on the floor should likely be in the position that day to spare some workers. Indeed, Figure 9, panel (a), shows the number of workers borrowed by a line grows with that line's percentage of absenteeism. Due to the shape of the relationship in Figure 8, panel (b), one would expect that managers desire to borrow would be low at lower level of absenteeism, and high at higher level of absenteeism. In other words, intensity of borrowing against absenteeism should have an increasing and potentially convex shape.

However, Figure 9, panel (b), which zooms in on the number of workers borrowed for each level of absenteeism, shows that the relationship between the number of workers borrowed and absenteeism is increasing, but concave.[89] A likely explanation is that desire to borrow does not translate fully into the realized number of workers borrowed. That is, this evidence is consistent with line managers facing difficulty in borrowing a large number of workers from any one partner or borrowing from many partners at once.

At relatively low levels of absenteeism, a manager may need 1 or 2 workers to return to full manpower. On the other hand, a line with 60 machines and 15% absenteeism would need to borrow as many as 5 workers to get back to peak efficiency. While it may be likely that a partner will be willing to part with 1 or 2 workers, it is unlikely to find a partner willing or able to part with a larger number of workers, given that no manager would want to relinquish so many workers so as to fall below 93% (as depicted in Figure 8, panel (b)).

Because managers can only ask so much from their partners, we see that the average number of workers borrowed is concave in absenteeism, reflecting the duality between their own need and the lending capacity of their partners. On the other hand, a manager could borrow from several partners each in the position to share a small number of workers. However, as we show below, line managers actively trade with only a few other managers, consistent with partnerships being costly to establish and maintain.

Note that there is heterogeneity in the number of workers borrowed. Since managers do not always borrow, Figure 9, panel (b), may give the false impression that managers borrow very few workers. The unconditional average number of workers borrowed is 1.9 (SD 2.95) with the 5^{th} and 95^{th} at 0 and

[89] Managers sometimes borrow at low absenteeism level when they have critical operations to fill. Some garments may require a specialized task that only a few key workers can do. Therefore, lines may borrow a specialized worker every now and then to fill this operation that none of their workers can do.

7 workers borrowed respectively. Conditional on borrowing, managers borrow on average 3.38 workers (SD 3.24) with the 5^{th} and 95^{th} corresponding to 1 and 9 workers respectively.

9.5 Absenteeism affects productivity despite (limited) borrowing

Next, we investigate whether these apparent limitations to borrowing in the presence of large absenteeism shocks translate into limitations on the ability to mitigate the impacts of absenteeism on productivity. We regress line-level efficiency on *home line* absenteeism, noting that observed efficiency is realized net of any borrowing. Large common absenteeism shocks across the factory floor would generate impacts on productivity; however, if managers are able to fully smooth the effect of their idiosyncratic absenteeism by way of borrowing workers, a manager's own absenteeism should not impact the line productivity after controlling for aggregate absenteeism.

Table 13 shows that even after accounting for most aggregate absenteeism shocks at the factory floor level by way of a broad array of fixed effects, a line's idiosyncratic absenteeism still impacts its productivity. We find that a 10 percentage-point increase in absenteeism decreases efficiency by roughly 4 percentage points. That is, risk-sharing among managers appears far from perfect.[90] In Appendix U, we show that these findings are robust (and indeed statistically equivalent) when using an instrumental variable (2SLS) analysis. We also check that the incidence of absenteeism shocks is balanced across

[90] We also run an analogous regression with the most stringent possible fixed effects (line, unit, and floor by date) to fully account for daily floor-level shocks. The point estimate is -0.452 (SE=0.043 when clustering at the line level and SE=0.039 with line and date clusters). Hence, the coefficient is is still highly significant even when accounting for daily floor-level shocks, further confirming that absenteeism is not smoothed perfectly on average.

lines and managers of varying productivity level using manager fixed effects estimates obtained from an AKM specification (Abowd et al., 1999). Moreover we include manager fixed effects in all regressions to account for differences in manager quality. These fixed effects absorb demographic characteristics and skills of managers as well as the size and composition of their pools of home line workers.

Table 11: Productivity losses from absenteeism

	Efficiency (q/target)		
	(1)	(2)	(3)
Percentage of Absenteeism	−0.3971	−0.4068	−0.4451
	(0.0374) ***	(0.0307) ***	(0.0317) ***
	[0.0381] ***	[0.0311] ***	[0.0321] ***
Observations	12737	12737	12737
Mean of Y	49.09	49.09	49.09
SD	15.85	15.85	15.85

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress daily line-level efficiency on the line's percentage of absenteeism. Both variables are on a scale of 0-100. We cluster the standard errors reported in parentheses at the manager level. In square brackets, we report 2-way clustered standard errors with one cluster for managers and one for dates. In column 1, we include manager and unit fixed effects to absorb time-invariant characteristics of the managers and the units. In column 2 and 3, we also include year, month, and day of the week fixed effects to account for common seasonality and growth dynamics in productivity and absenteeism across units. In column 3, we also include fixed effects for the style of garments produced.

Using a subset of days for which we have worker bonus payment data and the same IV strategy as that in Appendix U, we find that workers have a 25% chance of receiving a productivity bonus on average, but this probability falls by 2.1 percentage points for every percentage point increase in absenteeism (or roughly 14 percentage points for a 0.5 SD increase in absenteeism).[91] This result shows that the negative impact on productivity of absenteeism not only affects the firm, but also reduces the welfare of the workers who show up for

[91] The average unconditional (i.e., including 0s) daily productivity bonus is approximately 10 rupees and it falls by 0.2 for every percentage point increase in absenteeism.

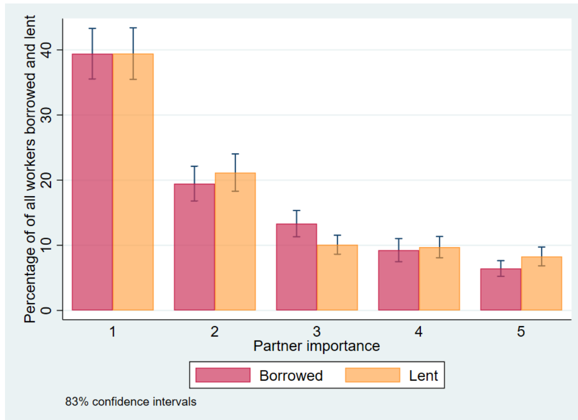
work. It also reinforces that managers, who are also eligible for the productivity bonus payment, have an incentive to not lend workers on any given day suggesting that, if they are still willing to lend workers, the value of being able to borrow workers in the future must be large.

9.6 Many potential trading partnerships are left unrealized

The previous section indicates that although managers exchange workers to cope with absenteeism, the trades are not sufficient to completely mitigate the impacts of absenteeism on productivity. We next document that managers seem to forego many potential partnerships. If we rank a manager's partners by the number of times they have exchanged workers over the span of the data, we find that 72% of all workers traded are exchanged with the three most frequent partners.

Moreover, managers are only ever observed (in the span of our data) forming a few trading partnerships. Under the definition that managers formed a partnership if they ever exchanged at least 2 workers a month for 4 months (consecutive or not), managers form 2 to 3 partnerships on average over the span of the data. If we assume that managers form a partnership if they ever traded and borrowed one or more workers between one another over the span of the data, we would conclude that managers form on average at most 5 partnerships. There are on average 20 to 22 managers per unit. Therefore, managers forgo approximately 15-17 partnerships on average in the most "generous" definition of a partnership. If we ignore incidental trades, managers forgo 17 to 19 active partnerships on average.

Figure 10: Percentage of all workers borrowed and lent by the importance of partners



Note: We calculate the frequency of trades between each manager (number of workers traded × the number of days they are traded). For each manager, we rank its partners by this trade frequency from the most frequent (rank 1) to the least frequent partner. Then, we compute the proportion of all workers borrowed and lent over the span of the data that comes from each of these partners. We plot 83.4% confidence intervals. 83.4% intervals that do not overlap indicate that 2 means are different at the 95% level. At the 95% level and a large number of observations $t = 1.96 \approx (\bar{X}_1 - \bar{X}_2)/\sqrt{se_1^2 + se_2^2}$. With common standard errors $\bar{X}_1 - \bar{X}_2 = 1.96\sqrt{2}se = 1.386se$ which corresponds to an 83.4% confidence interval on the normal distribution. Here, the intervals overlap within partner importance indicating that the exchanges are symmetric and that managers pay back on average the workers they borrow by lending back to their partners.

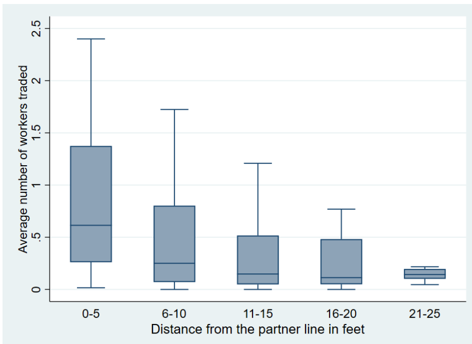
Figure 10 plots the average percentage of all workers borrowed and lent across managers by the importance of each partner. For each manager, we compute the frequency of trade for each partner. The most important partner (rank 1) is the partner a manager trades with the most often. The intensity of trade is not uniform across partners. Indeed, on average, 40% of all workers borrowed come from a single partner. Moreover, the percentage of workers borrowed falls rapidly with the rank of the partner clearly indicating that managers maintain active partnerships with only a few other managers. The same is true for the percentage of workers lent. The figure clearly indicates that relationships are symmetric in that a manager will borrow the same percentage that she will lend to a given partner on average. That is, managers pay back their partners when they borrow from them by lending them workers at a later time.

Managers tend to exchange workers with lines that are within a short distance on the factory floor. We find that 72% of the workers ever traded are with lines that are within 20 feet. We also find that managers tend to trade with managers that are similar to them in terms of demographic characteristics. For example, managers conduct nearly 66% of their trading with managers with a similar level of education and 71% of their trades with managers of the same gender.[92]

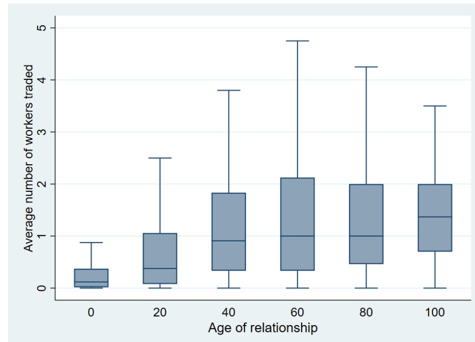
[92]From the data, we can tell whether the managers (1) didn't passed the 10th grade, (2) passed the 10th grade, (3) completed high school (passed the 12th grade), or (4), have a bachelor or higher degree. Managers have a similar level of education if they fall in the same category or are 1 category apart.

Figure 11: Average number of workers traded daily

(a) Distance from the partner line



(b) Age of the relationship with the partner line



Note: We compute the number of workers traded (borrowed +lent) daily from a line and each of its partner and plot the distribution by distance bins in feet in panel (a) and in age bins in panel (b). Age is defined by the number of days during which two lines have traded at least one worker with one another. Panel (a) only includes trades done within the same production floor since we do not have measures of distance across floors. We restrict the graphs to trades within 25 feet and within relationships no older than 100 days as few trades are observed beyond these points.

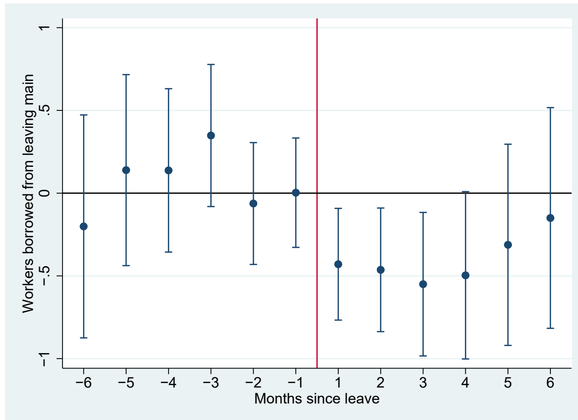
In Figure 11, we plot the interquartile range of the daily number of worker traded by pairs of lines by distance bins between the lines and by the maturity of the relationship as measured by the cumulative number of days they have traded at least one worker. The figure documents that distance is negatively related with trade, while maturity is positively related. Both distance and age appear to have a roughly linear relationship with trade.[93]

[93]Note that the relationships are virtually identical if we plot the number of workers borrowed or the number of workers lent on the vertical axis rather than the sum of the two. This is consistent with Figure 10 that suggest that managers repay the workers they borrow.

9.7 Trade breaks down when an important partner leaves

If the trade patterns observed indeed stem from relational contracting as we hypothesize, then we should expect that relationships break down when a partner leaves. On the other hand, no break would be expected if trades are planned centrally such that the identity of the lending line's manager is irrelevant. In Figure 12, we plot the coefficients from an event-study regression of the number of workers borrowed from a line's main trading partner before and after the partner line's manager leaves. We focus on the borrowing of lines which themselves do not experience any turnover to make the exercise easily interpreted and restrict attention to cases in which the main trading partner was stable over at least the one full month prior to the departure of the partner line's manager.

Figure 12: Workers borrowed from main partner lines with a departing manager



Note: We compute the average number of different workers borrowed weekly by lines without managerial turnover from important partners with a leaving manager six months before and 6 months after the leave. We regress the number borrowed on dummies for every month before and after the manager leaves and include unit, year, month, and lines fixed effects. The first month before (after) the manager leaves is composed of the first (last) three weeks of that month. The two weeks during which the manager separation occurs are the excluded dummy. We know that the separation occurs within those two weeks, but not the exact date. We plot 95% confidence intervals.

Figure 12 shows that before the manager separation occurs, trade is flat or weakly increasing, followed by a sharp reduction in trade when the manager of the main trading partner line leaves and a gradual recovery thereafter. It takes at least 3 or 4 months for trade to recover. Such a break in trade is consistent with relational contracts, as it is less likely that managerial turnover would affect how a central planner moves workers around in response to absenteeism.

10 Theory and Empirical Predictions

In this section, we posit a simple model of managers' interactions and generate empirical predictions which we test in the subsequent section. Most of the seminal models of relational contracts involve a transfer of utility between risk neutral agents; while in our setting managers transfer workers who are inputs in a concave production function. Accordingly, we propose a novel simple framework that better represents the context at hand, drawing elements and intuition from many of the established models of relational contracting.

The model is designed to match the qualitative features of the context described above. We assume that managers of production lines have private information about their types (reliable or unreliable) and the number of home line workers present on a given day. Managers can borrow or lend workers from their main partners depending on the number of home line workers present on their and partners' lines, but contract enforcement is infeasible (MacLeod and Malcomson, 1989, Levin, 2003). Transaction costs affect the intensive and the extensive margin of the number of workers borrowed or lent. Finally, beliefs about main partners' types are updated following Bayes' rule.

We first turn to the analysis of the model with symmetric managers (i.e., all managers are reliable). The incentive compatibility constraint of the model clarifies how the number of home line workers present, the outside option, and transaction costs affect the number of workers borrowed/lent between main partners. Next, we analyze the transition path to a stationary contract of the model with uncertainty over managerial type. On the convergence path, the incentive compatibility constraint suggests a positive relationship between the number of workers borrowed or lent and the maturity of the relationship.

10.1 Setup

We study a set of managers, $\mathcal{K}$, who live forever and share a common discount factor δ. Time is discrete, indexed by $t = 0, 1, \ldots$. Each production line has the same number of home line workers, $\bar{y}$, and lines suffer from random absenteeism shocks. That is, in any given period, a certain number of these workers report for work (i.e., are present) – this quantity is denoted as $y_{i,t}$, where $y_{i,t} \in \{y_1, y_2, \cdots, y_n\}$ and $y_1 < y_2 < \cdots < y_n$ with $y_n \equiv \bar{y}$.[94]

Each production line produces $f(y_{i,t} - \theta_{ij,t})$ units of garments in period t, where $\theta_{ij,t}$ is the net number of workers transferred from manager i to manager j, and $f(\cdot)$ is a production function such that $f' > 0$ and $f'' < 0$ for all $y_{i,t} - \theta_{ij,t} > 0$.[95]

We assume that $y_{i,t}$ is privately known by the manager of production line i and follows a discrete distribution, $\pi_i(\cdot)$, independent across time and of the state of their peers, $y_{-i,t}$ and $\pi_{-i}(\cdot)$. We assume that distribution functions are symmetric such that $\pi_i(\cdot) = \pi(\cdot)$ for every line $i \in \mathcal{K}$. In particular from these assumptions, we obtain that $P(y_{i,t} = y_l, y_{j,t} = y_m) = P(y_{i,t} = y_l)P(y_{j,t} = y_m) = \pi(y_l)\pi(y_m)$ for every line i and $j \in \mathcal{K}$ and $l, m = 1, \cdots, n$, with l, m being the states associated with the number of home line workers present. For simplicity, we denote this probability as π_{lm} and assume that $\pi(y_l) > 0$ for each $l = 1, \cdots, n$.

There are two types of managers: reliable (R) and unreliable (U). The measure of reliable managers is γ_0, and the measure of unreliable managers is $1 - \gamma_0$.[96] Managers privately know their own type and have a prior about their partner's type γ_0, which they update each period.[97] Reliable managers always

[94] Our model is in essence similar to Coate and Ravallion (1993) and Ligon et al. (2002), but differs in two important ways: (i) hidden information is critical in our setting – we thus model private managerial type (reliable or unreliable); (ii) transaction costs of transferring workers affects both the intensive and extensive margins of trade.

[95] Note that the net number of workers transferred, $\theta_{ij,t}$, can be positive (lend workers) or negative (borrow workers).

[96] This is a fairly standard assumption in the relational contracting literature; see, e.g., Yang (2013), Halac (2012), and Malcomson (2016).

[97] Belief updating is explained in detail in Section 4.3.

tell the truth about the current number of home line workers that they have. Unreliable managers lie with probability $1 - \rho$ about their current number of home line workers, whenever their state is better than their partner's state. This probability is known to both parties and constant over time.[98]

In each period, managers are matched randomly and establish (or continue in) bilateral relationships.[99] In a potentially ongoing relationship, manager i agrees to help manager j if i is in a (reported) better state (i.e., higher proportion of home line workers present) than j; in return, j agrees to help i when their states are reversed in the future. At the beginning of the period, the number of home line workers that manager i has is unknown to manager j, and vice versa. At the end of the period managers confirm if their partner told the truth, then, a match can be dissolved endogenously if either party in the current relational contract decides to leave the match.[100]

[98]This leads to a simple (and fairly attractive) alternative interpretation for the model: suppose that there are two types of workers, having high and low productivity, respectively. Assume that low productivity workers do not increase production, i.e., managers care only about high productivity workers' absenteeism, which we can denote as $y_{i,t}$. Also assume that reliable and unreliable managers always tell the truth about the current number of high productivity workers that they have. However, unreliable managers transfer $\theta_{ij,t}$ high productivity workers with probability ρ, and transfer low productivity workers (represented by $\theta_{ij,t} = 0$) with probability $1 - \rho$, whenever their state is better than their partner's. The model's analysis would proceed in the same manner, but could be interpreted as understanding the optimal flow of high productivity workers in this context. This relates to several important papers in the theoretical relational contracting literature. For example, Yang (2013) studies non-stationary relational contracts in a repeated principal-agent game. That model is similar to ours in that workers can be of high or low type, but high-type workers can choose a high effort $\bar{e} > 0$, while low-type workers exert low effort 0. Malcomson (2016) studies relational incentive contracts in a principal-agent setting where agents are heterogenous and have private information over their types. Malcomson's formulation differs from Yang's – among others – in that workers' types in the former model are continuously distributed.

[99]For simplicity of exposition, we posit that partnership formation is exogenous (i.e., manager pairs are determined randomly), and we also shut down experimentation. Note also that much of the canonical relational contract theory assumes quasi-linear utility and monetary transfers that can substitute for variation in continuation payoffs (Levin, 2003). Given our empirical context, it is natural to model risk averse agents; in this sense our model is positioned a bit closer to the literature on risk-sharing and informal insurance (Coate and Ravallion, 1993).

[100]We can also assume that at the end of the period managers confirm if their partner told the truth with probability $\lambda \in (0, 1)$. The predictions of the model remain intact since

Finally, we assume that there is a transaction cost, $c_{ij} \geq 0$, which is ij-specific and constant across states.[101] Transaction costs affect the intensive margin (i.e., the number of workers borrowed or lent) but can also affect the extensive margin if they are large enough (i.e., the frequency of transfers between i and j).

Contracts that are contingent on the state of the line, $y_{i,t}$, are not enforceable, and there is no information flow between matches. Moreover, we assume that a manager's history of transfers is not observable outside of a given match (i.e., to other fellow managers).

10.2 Timing

At the beginning of the period, nature selects the states of each production line, that is, $Y(t) = (y_{i,t}, y_{j,t})$ for $i, j \in \mathcal{K}$, and U-type managers know if they will tell the truth or not. After observing the history of the game, managers meet and declare their state. If the state of manager i is better than the state of j, there are three potential outcomes:

(1) If i is an R-type manager and transaction costs are low (compared to i's state), i chooses a transfer some of his own home line workers to manager j, denoted as $\theta_{ij,t}$. Transfers are realized, and managers continue in the ongoing relationship.

(2) If i is an R-type manager and the transaction cost, c_{ij}, is high (compared to i's state), i does not transfer any of his home line workers to manager j, i.e., $\theta_{ij,t} = 0$. Then managers continue in the ongoing relationship.

unreliable managers every period lie with probability $1 - \rho$ about the current number of home line workers. For simplicity we assume that $\lambda = 1$.

[101] For example, the physical and demographic distances between i and j.

(3) If manager i is a U-type, he does not tell the truth about his state with probability $1-\rho$, then, i does not transfer any home line workers to manager j and manager j ends the relationship at the end of the period. If i tells the truth, the outcome can be (1) or (2).[102]

Finally, managers update their beliefs about their partner's type, period t ends and period $t+1$ begins.

10.3 Strategies, belief updating, and incentive constraints

As the solution concept we adopt symmetric perfect public equilibrium (SPPE).[103] A strategy for a manager of type $u \in \{U, R\}$, σ^u, is a decision rule about whether to accept the current contract and the transfers to his partner as a function of the (within-dyad) history of transfers. A relational contract consists of a strategy profile $\sigma = \left(\sigma^R, \sigma^U\right)$. Denote γ_t^{ij} as manager i's belief that his partner j is an R-type manager, given the history of t interactions. By Bayes' Rule, after t interactions from i to j, i's belief about the probability that j is an R-type is

$$\gamma_t^{ij} = \frac{\gamma_0}{\gamma_0 + (1-\rho)^t (1-\gamma_0)}.$$

In an ongoing relationship, suppose i's reported state in period t is better than j's state. If i is an R-type manager and truthfully reports his state, future payoffs from period t onward for a relationship are given by:

[102] Note that reliable managers and unreliable managers that tell the truth, can shirk and quit the relationship in period t if the relational contract is no longer incentive compatible.

[103] We follow Yang (2013) in this solution concept. By symmetry, we mean that all managers adopt the same strategy. Public strategies require that each agent's strategy only depends on the public history within the current relationship, since previous relationship history is not observable.

$$U_{i,t}^{R}\left(\boldsymbol{\theta}_t;\gamma_t^{ij}\right)=f\left(y_{i,t}-\theta_{ij,t}\right)-c_{ij}+\delta U_{i,t+1}^{R}\left(\boldsymbol{\theta}_{t+1};\gamma_{t+1}^{ij}\right).$$

If i does not tell the truth and therefore does not lend j workers, future payoffs from t onward for a relationship are given by

$$U_{i,t}^{S}\left(\boldsymbol{\theta}_t;\gamma_t^{ij}\right)=f\left(y_{i,t}\right)+\delta V\left(n_i\right),$$

where $V\left(n_i\right)$ is the outside option of manager i, which depends on the number of outside relationships, n_i.

The incentive compatibility constraint is thus:

$$f\left(y_{i,t}\right)-f\left(y_{i,t}-\theta_{ij,t}\right)+c_{ij}\leq\delta\left(U_{i,t+1}^{R}\left(\boldsymbol{\theta}_{t+1};\gamma_{t+1}^{ij}\right)-V\left(n_i\right)\right). \tag{12}$$

Then, an *optimal dynamic relational contract*, $\{\boldsymbol{\theta}_t^*\}_{t\in\mathbb{N}}$, is the maximum of $U_{i,0}^{R}\left(\{\boldsymbol{\theta}_t\}_t;\gamma_0\right)$ subject to the incentive compatibility constraints (12) for all t, where $U_{i,0}^{R}\left(\{\boldsymbol{\theta}_t\}_t;\gamma_0\right)$ is the present value of the expected utility over time, defined in equation (V.10).[104]

[104]Related work studies nonstationary relational contracts with a focus on informational aspects. For example, McAdams (2011) considers a model of partnerships in the form of complete information stochastic games with voluntary exit where payoffs are subject to a persistent initial shock—these shocks follow a general stochastic process. Under these hypotheses, the social welfare-maximizing equilibrium induces a dating process in which all parties enjoy full potential equilibrium gains. In contrast, shocks determining managers' payoffs in our model follow a discrete distribution that is independent across time and states of different agents. Halac (2015) considers a principal-agent model where the principal makes an investment at the beginning of the relationship. The returns to this investment can be unobservable. The author shows that if the agent cannot observe principal's investment returns, then the agent cannot capture these returns.

10.4 Symmetric Stationary Relational Contracts

To study the features of a *symmetric stationary relational contract* in this context, suppose first that $\gamma_0 = 1$, that is, all managers are reliable so that they do not need to update their beliefs.[105] The incentive compatibility constraint in this case is thus

$$f(y_i) - f(y_i - \theta_{ij}) + c_{ij} \leq \delta\left(U^R(\boldsymbol{\theta}) - V(n_i)\right). \tag{13}$$

Let α_{ij} be the value of y_i for which equation (15) below is satisfied for positive values of θ_{ij}. The first best allocation $\hat{\boldsymbol{\theta}}$, where each $\hat{\theta}_{ij} = \frac{y_i - y_j}{2}$ if $y_i > \max\{y_j, \alpha_{ij}\}$, and $\hat{\theta}_{ij} = 0$ in any other case, is the value of $\boldsymbol{\theta}$ that maximizes the function $U^R(\cdot)$ over the set of all possible allocations. Since the probabilities of observing a given state are symmetric across lines, we can restrict our search to the space of symmetric relational contracts where each $\boldsymbol{\theta} \in \mathbb{R}^{n^2}$ is characterized by a vector $\overrightarrow{\theta} = (\theta_{21}; \theta_{31}, \theta_{32}; \cdots; \theta_{n1}, \cdots, \theta_{nn-1}) \in \mathbb{R}^d$ with $d = n(n-1)/2$. The transfer in a stationary relational contract, $\boldsymbol{\theta}^*$, is such that it maximizes $U^R(\cdot)$ (see equation (V.1) in Appendix V) when restricting the domain to all symmetric non-negative allocations such that (13) is satisfied. Such a value $\boldsymbol{\theta}^*$ exists and it is unique because $U^R(\cdot)$ is strictly concave, and the restricted domain is a convex and compact subset of $\mathbb{R}^d$.[106]

Proposition 1. There exists a unique stationary contract $\boldsymbol{\theta}^*$ characterized by the following:

[105] Note that if both managers are reliable, as $t \to \infty$, the relational contract converges with probability 1 to a *symmetric stationary relational contract*, in which both managers beliefs, γ_t^{ij}, converge to 1.

[106] For simplicity, we assume that the transaction costs between i and j are the same for both lines. Similarly, we assume that the outside option are the same for line i and j, i.e., $V \equiv V(n_i) = V(n_j)$.

$$\theta_{ij}^{*} = \min\left\{\hat{\theta}_{ij}, H\left(y_i, c_{ij}, \delta\left(U^R\left(\boldsymbol{\theta}^*\right) - V\right)\right)\right\}, \tag{14}$$

where $H(\cdot)$ is such that (y_i, c_{ij}, w) satisfy

$$\Delta\left(y_i, c_{ij}, H\left(y_i, c_{ij}, w\right)\right) \equiv f\left(y_i\right) - f\left(y_i - H(y_i, c_{ij}, w)\right) + c_{ij} - w = 0, \tag{15}$$

with $w = \delta\left(U^R\left(\boldsymbol{\theta}^*\right) - V\right)$, and $\hat{\theta}_{ij}$ is the first best allocation.

Proposition 1 shows that given $y_i > y_j$ and c_{ij}, there exists a stationary equilibrium in which the optimal transfer for each y_i, c_{ij} is uniquely defined by (15). Note that the optimal transfer is always less than or equal to the efficient transfer, $\hat{\theta}_{ij}$.

From (15), it follows that the number of home line workers transferred from i to j increases as the state of i increases, as long as the first best allocation is never achieved. That is, as the state (proportion of home line workers present) of line i increases, there is less pressure on the incentive constraint, which allows manager i to increase the number of workers transferred.

10.5 On the transition path to the stationary contract

If $\gamma_0 < 1$, note that if both managers are reliable, as $t \to \infty$, the relational contract converges with probability 1 to a *symmetric stationary relational contract*. From (12), it follows that on the transition path to steady state, as the number of transfers increases, the present value of the relationship, $U^R_{i,t+1}\left(\boldsymbol{\theta}_{t+1};\gamma^{ij}_{t+1}\right)$, increases as well, since the posterior beliefs of partners being reliable increases. As a result, the number of workers transferred from line i to j (and vice versa) also increases. We present this result formally in the next proposition.

Proposition 2. There exists $\underline{\theta} > 0$ such that an optimal dynamic relational contract $\{\boldsymbol{\theta}^*_t\}_t$ is monotonic if $\theta^*_{ij,t} > \underline{\theta}$ for all $t \in \mathbb{N}$.

Proposition 2 shows that there exists a value $\underline{\theta} > 0$ such that if $\theta^*_{ij,t} > \underline{\theta}$, a *monotonic optimal dynamic relational contract* arises if the allocation is below the first best allocation defined above, i.e for all $t \in \mathbb{N}$, $\theta^*_{ij,t} < \hat{\theta}_{ij}$.[107] From the proof of Proposition 2 in Appendix V, it is easy to show that given the value of γ_0, and conditions on ρ and δ, there is a period T after which $\theta^*_{ij,T+k}$ is monotonic for any $k \in \mathbb{N}$.[108]

If any manager (or both) is U-type, the relational contract will dissolve as $t \to \infty$. That is, the number of transfers may increase as the number of periods in which managers tell the truth increases (i.e., they borrow/lend workers from their partners or the difference in the lines' state does not compensate the transaction costs).[109] Eventually, U-type managers will be found out, and those relationships will end.

[107] In the proof of Proposition 2 we show that $\underline{\theta}$ depends on the range of the y_i's. In particular, the larger the distance between the y_i's, the smaller the value of $\underline{\theta}$.

[108] Note that, in general, dynamic relational contracts are quasi-monotonic (see, e.g., Yang (2013)).

[109] Board (2011) studies a game in which a principal and a set of agents trade over time under the threat of holdup. He shows that the optimal relational contract induces loyalty (i.e., the principal is loyal to the agents she has traded with, while being biased against new agents).

10.6 Summary of Predictions

To summarize, the following are the five key predictions from this model that we take to the data. The first three predictions pertain to steady state comparative statics. Suppose that the number of home line workers present for line j is greater than the number of home line workers present for line i (i.e., $y_i < y_j$). Then, in a stationary relational contract, the number of workers borrowed by manager i from manager j...

- Prediction 1: ...decreases as i's state (i.e., increases with absenteeism on i's line) improves (or i's absenteeism worsens) relatively to j's.
- Prediction 2: ...increases as the transaction cost between i and j decreases.

  Also, in a stationary relational contract:
- Prediction 3: As transaction costs decrease, the frequency of transfers between i and j increase.

The fourth and fifth prediction pertains to the transition path to the steady state. In particular, on the convergence path, as the maturity of the relationship (the cumulative number of transfers between managers i and j) increases:

- Prediction 4: ...the amount borrowed by manager i from manager j also increases.
- Prediction 5: ... the frequency of transfers between i and j increase.

Although we do not structurally estimate our relational contract model, we can still empirically evaluate the model's predictions against some obvious alternative models. The first alternative framework that can be tested is that of a central planner. Note that the planner would not care about some of the transaction costs (e.g., the distance) or the length of the relationship (see, for example, the planner problem developed for the same context in Adhvaryu et al. (2021a)). Thus, Predictions 3, 4, and 5 would not hold if higher-level management acts as a central planner reallocating workers across production lines. Another alternative model we can rule out is risk-pooling, as only the aggregate number of workers would be significant which is not what we show in Table 13. Finally, we can rule out autarky as we observe relationships being formed in the data as documented in Figure 10.

11 Empirical Tests of Model Predictions

In this section, we formally bring the model's predictions to the data. The model yields predictions for how the number of workers borrowed by manager i from partner manager j should vary with the absenteeism on line i relative to absenteeism on line j, the maturity of the partnership with manager j, and the transaction cost.[110] In particular, the model predicts that manager i should borrow more workers from partner j as line i's absenteeism increases relatively to j''s and as the partnership matures. Relationship maturity is defined as the number of times a pair has exchanged workers. With at least 6 months of daily data, each pair can interact over 140 times, which allows us to track the evolution of managerial trading behavior over a large number of potential interactions. Finally, we predict that manager i should borrow fewer workers from partner j as the cost of the transaction between i and j rises.

[110]Note that "manager" and "production line" are used interchangeably; that is, whenever we refer to manager i, we mean the manager of production line i.

11.1 Empirical Strategy

As discussed in section 9, the dataset we use to test the predictions consists of a dyadic panel of all potential manager partnerships on a production floor for every production day.[111] Our model predicts that this trade decision depends on the demographic similarity of the managers and the physical distance between the production lines (transaction cost). In this sense, our empirical setup is similar to the canonical gravity model, which has the basic conclusion that trade between two countries is inversely proportional to their distance (Anderson and Van Wincoop, 2003, Anderson, 2011, Chaney, 2018, Donaldson, 2018). We follow this literature in estimating the following log-gravity equation:

$$\begin{aligned}\theta_{ijuft} = \alpha + \beta_1 \frac{(\%\, Abs_{iuft} - \%\, Abs_{juft})}{2} + \beta_2 ln(Maturity_{ijuft}) + \beta_3 ln(Dist_{ijuf}) + \beta_4 Gender_{ijuf} \\ + \beta_5 Education_{ijuf} + \beta_6 ln(Age\, diff_{ijuf}) + \beta_7 ln(Experience\, diff_{ijuf}) + \Phi + \varepsilon_{ijuft},\end{aligned} \tag{16}$$

where the subscript i refers to a given manager and j to a potential partner on the floor. Subscript u indicates the unit or factory, f the floor within the factory, and t indicates the date.[112] Our dependent variable, θ_{ijuft}, is the number of workers borrowed by manager i from manager j on floor f in factory unit u on date t. In line with the model, our main independent variable

[111] As we note in section 9, negligible trade occurs across floors; accordingly, we focus on pairs of managers located on the same factory floor. As such, the distance variable is defined as the number of feet between two lines on a factory floor.

[112] We abstract from capital input and material input choices: the machines and materials needed to produce a given style are decided at the firm level and are readily available to production lines, such that conditional on style, there is no variation across production lines in the quantity and quality of machines and materials available. Therefore, we note that the identification issues around the endogenous choice of capital and materials highlighted by the literature on production function estimation do not apply in this case (Ackerberg et al., 2015).

is the average difference in absenteeism between manager i and its partner j on date t. Our model predicts that the number of workers borrowed is larger the worse is i's state compared to j's state.[113] We also include the natural log of the maturity of the relationship between the managers, the natural log of the distance between their lines, and binary variables for whether the managers are of the same gender and have the same level of education[114] as well as the natural log of the (absolute) difference in age and experience of the managers in managing their current lines, which are proxies for so-called identity-based distance.[115] In some specifications we include the natural log of the number of days since i's order started to account for learning-by-doing.[116]

In addition to physical and demographic distance between managers, another dimension that might determine heterogeneity in trading responsiveness (both borrowing and lending) is each managers' quality as studied in Adhvaryu et al. (2021d). We document in Figure U.3 that absenteeism is balanced across managerial quality and we include manager fixed effects (as discussed further below) to ensure that manager quality differentials are not driving our results on trading partnerships. Nevertheless, we do investigate in additional results below the degree to which different dimensions of managerial quality predict trading activity.

The matrix Φ corresponds to varying sets of cross-sectional and temporal fixed effects depending on the specification used. In particular, we include

[113]Our model yields prediction for cases where i's absenteeism $\geq j$'s absenteeism. In our main results we consider only theses cases. In Appendix Q, we show that the results hold if we include cases where j's absenteeism $> i$'s absenteeism.

[114]Managers have a similar level of education if they fall in the same category as defined as follows: (1) did not pass 10th grade, (2) passed 10th grade, (3) completed high school (passed 12th grade), or (4), have a bachelor's or higher degree.

[115]Recall that the age difference and the difference in experience managing the line are not correlated $\rho = 0.0446$.

[116]We take the natural log of the variables listed above and add 1 in order to not exclude cases where the variables are equal to 0.

unit, manager i and manager j fixed effects as well as year, month and day of the week fixed effects to account for common seasonality in absenteeism across managers. For all regressions, we report three types of standard errors. First, we cluster at the manager pair level. These standard errors are reported in parentheses (163 clusters). Second, we use a two-way clustering strategy with one cluster for the manager pair (163 clusters) and one cluster for the date (314 clusters). These two-way-clustered standard errors are reported in square brackets. Finally, in curly brackets, we report two-way-clustered standard errors with one cluster for each manager in the pair (73 clusters each). The different approaches to clustering employed correspond to the most common strategies used when dealing with dyadic data.

Since the left hand side is the count of the number of workers borrowed and that many partnerships are left underutilized, estimating this equation by OLS is known to yield inconsistent estimates. Instead, following the trade literature, we estimate the model using Poisson Pseudo Maximum Likelihood, or PPML (see, e.g., Silva and Tenreyro (2006, 2011), Costinot et al. (2019), Bryan and Morten (2019)). Count models with instrumental variables in addition to fixed effects are known to suffer from incidental parameter problems and have been shown to be inconsistent (see Cameron and Trivedi (2013) and Beghin and Park (2021)). Therefore, we do not use the instrument directly in these dyadic gravity-style regressions. Rather we perform a series of checks presented in Appendix U to demonstrate the exogeneity of absenteeism in this context.

11.2 Results

Table 12 presents the results from the estimation of equation 16, and the results confirm each of the model's predictions, in turn. First, the results confirm that number of workers borrowed increases when i's state deteriorates compared to j's. Specifically, we find that when the average difference in the states increases by 1% (5%), the number of workers borrowed by manager i from manager j increases by 5-6% (28-34%).[117] To illustrate the size of the effect, consider a case where a manager has 1% absenteeism and borrows 1 worker from each of his 3 main partners who have no absenteeism. In other words, the main coefficient is 0.005 for all 3 main partners. The manager would borrow one more worker across the 3 partners, or 4 workers in total that day, if his absenteeism were to increase to 10.8-12.6%. If the manager's absenteeism were to rise to 24.8-29.2%, he would borrow one additional worker from each of his main partners, for a total of 6 workers borrowed that day.

We find that a manager in a relationship that is more mature by 10 days compared to the average relationship, borrows approximately 34% more workers from that partner.[118] Hence, a manager that borrows one worker in an average partnership would borrow one more worker every 3 days in a partnership more mature by 10 days or 1 more worker every day from a partnership more mature by 28 days. All else equal, a manager borrows approximately 29% less from a manager that is 12 feet away compared to a manager 3 feet away.[119] Or, a manager who borrows one worker from a line 15 feet away would borrow one additional worker each day from a line only 3 feet away.

[117] The first coefficient is in decimals. The equation for the number of workers borrowed is $\theta_{ij}^1 = e^{\beta_1 x_1 + X\beta}$. Consider a case where the main coefficient, x_1, increases by 1% (0.01), then $\theta_{ij}^2 = e^{\beta_1 x_1 + \beta_1 0.01 + X\beta}$. Therefore, $\theta_{ij}^2 - \theta_{ij}^1 = (e^{\beta_1 0.01} - 1)\theta_{ij}^1$ and the percentage change in the number of workers borrowed is given by $100 \times \frac{\theta_{ij}^2 - \theta_{ij}^1}{\theta_{ij}^1} = 100 \times (e^{\beta_1 0.01} - 1)$. Using the coefficient in column 1, we find that when x_1 increases by 1%, the number of workers borrowed increases by $100 \times (e^{5.81 \times 0.01} - 1) = 5.98\%$. From column 3, we find that borrowing increases by $100 \times (e^{5.91 \times 0.01} - 1) = 5.03\%$.

[118] The average maturity of partnerships is 40.06 days. 10 days represent a 24.96% increase from average. We find that this increase translate into a $100 \times (e^{1.308 \times ln(1.2496)} - 1) = 33.83\%$ increase in borrowing in column 2 and $100 \times (e^{1.3117 \times ln(1.2496)} - 1) = 33.95\%$ in column 3.

[119] The percentage change is $100 \times \frac{(e^{-0.246 \times ln(12)} - e^{-0.246 \times ln(3)})}{e^{-0.246 \times ln(3)}} =$ -28.93% in column 2 and -28.89% in column 3.

Next, we investigate whether the behavior of managers is also affected by their demographic differences. We find that managers borrow 61-63% less from partners of different gender than with managers of the same gender.[120] This means that a manager borrowing 1 worker from a partner of a different gender would borrow 1.6-1.7 additional workers daily from a partner of the same gender. Additionally, when looking at the coefficients in column 2 and 3, we find that a manager borrows approximately 16% less from managers with a different level of education. A manager borrowing 1 worker from a partner with a different level of education would borrow 1 additional worker from a partner with the same level of education every 5 days.

Finally, we find that differences in age and experience also affect the trade behavior of the managers. Indeed, a manager tends to borrow 6.5-11% less from managers 10 years different in age than with managers within 1 year age difference.[121] That is, a manager borrowing 1 worker from a partner younger or older by 7 years would borrow 1 additional worker from a partner 1 year his junior or senior every 10 days. Similarly, managers tend to borrow more from partners with similar levels of experience managing their current line. They tend to borrow 23-33% less from managers with 5 years difference in experience than from managers with just 1 year difference in experience. That is, a manager borrowing 1 worker from a partner with a 5 year difference in experience would borrow 1 additional worker every other day from a partner with the same level of experience.[122]

[120] When the dummy variable goes from 0 to 1, the effect is $100 \times (e^{\beta} - 1)$ percent.

[121] The percentage change is $100 \times (e^{-0.029 \times ln(10)} - 1) =$ -6.46% in column 1, and 10.9% in column 2 and 3.

[122] Recall that in subsection 8.6, we showed that the location of the managers in the factory is unrelated to how similar they are to managers around them. We also showed that physical distance and the demographic distance variables are highly uncorrelated between one another which could have limited our ability to interpret the coefficients of the regression.

Table 12: Tests of model predictions

	Number of workers borrowed		
	(1)	(2)	(3)
$(\%Abs\, i - \%Abs\, j)/2$	5.8103	5.2897	4.9104
	(2.0057) $***$	(1.7518) $***$	(1.6650) $***$
	[2.0167] $***$	[1.7663] $***$	[1.6870] $***$
	{2.5503} $**$	{2.0001} $***$	{1.9338} $**$
log(Maturity of relationship)	0.3475	1.3079	1.3117
	(0.1179) $***$	(0.0871) $***$	(0.0866) $***$
	[0.1193] $***$	[0.0880] $***$	[0.0875] $***$
	{0.1344} $***$	{0.0933} $***$	{0.0932} $***$
log(Distance)	−0.8361	−0.2463	−0.2459
	(0.1177) $***$	(0.0842) $***$	(0.0839) $***$
	[0.1191] $***$	[0.0860] $***$	[0.0857] $***$
	{0.1314} $***$	{0.0954} $***$	{0.0949} $***$
	Identity-based distance		
Different gender	−0.9506	−0.9934	−0.9978
	(0.2415) $***$	(0.2087) $***$	(0.2114) $***$
	[0.2357] $***$	[0.2049] $***$	[0.2081] $***$
	{0.3378} $***$	{0.3550} $***$	{0.3580} $***$
Different education	−0.5023	−0.1835	−0.1836
	(0.1282) $***$	(0.0913) $**$	(0.0911) $**$
	[0.1299] $***$	[0.0924] $**$	[0.0923] $**$
	{0.1243} $***$	{0.0811} $**$	{0.0808} $**$
log(Difference in age of managers)	−0.0290	−0.0500	−0.0500
	(0.0185)	(0.0157) $***$	(0.0157) $***$
	[0.0184]	[0.0156] $***$	[0.0156] $***$
	{0.0192}	{0.0161} $***$	{0.0162} $***$
log(Diff. in exp. on the line)	−0.1611	−0.2564	−0.2567
	(0.0969)$*$	(0.0785) $***$	(0.0783) $***$
	[0.0958]$*$	[0.0770] $***$	[0.0768] $***$
	{0.0789} $**$	{0.0818} $***$	{0.0816} $***$
Observations	27560	27560	27560
Mean of Y	.215	.215	.215
SD	.853	.853	.853
Effect when X1= 1%	5.98 %	5.43 %	5.03 %
Effect when X1= 5%	33.71 %	30.28 %	27.83 %

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress the daily number of workers borrowed at the manager-pair level on the average difference in absenteeism in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers are of different gender, a dummy for whether they have a different level of education, on their log age difference, and on their log difference in their experience managing their respective lines. We include dyads on a same floor for which the average difference in absenteeism in the pair is greater or equal to 0. In parentheses, we report standard errors clustered at the pair level. In square brackets, we report 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each managers as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 adds to the specification in column 2 the natural log of the number of days since the borrower's order started to control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

On the whole, these results show that managers do indeed borrow more from their partners as they are hit by stronger absenteeism shocks than their partners. The positive coefficient of the maturity of the relationship indicates that trust evolves with the number of interactions between the managers. Additionally, the results suggest that both physical and identity-based, or demographic, distances impose substantial barriers on relationship formation and dynamics. We show in Appendix Q that the results are virtually identical when controlling for whether the two lines in a pair are working on the same style of garment. This evidence helps to alleviate concerns that trading between lines closer to each other on the factory floor and/or otherwise more likely to trade intensively does not simply reflect the probability of working on the same order, which anyway happens rarely. Finally, in Appendix R, we look at whether trade patterns differ with respect to high and low efficiency workers. As is predicted by a generalized version of the model in which workers are of differing quality, we find that managers are more selective of the partners with whom they trade their higher productivity workers.

Table Q.1 reports the result of a logistic regression and shows how the previous variables affect the odds ratio of borrowing. The direction of the effects we found for the intensive margin are preserved here along the extensive margin. From column 2 and 3, we find that when the average difference in absenteeism is 5%, the odds of manager i borrowing from manager j increase by 27% compared to a scenario where both managers have the same level of absenteeism. We find that the odds of borrowing are 182% larger in a partnership twice as mature. The odds that i borrows from j decrease by 34.5% if j is 6 feet away from i rather than 1 foot away. The odds of borrowing between managers of a different gender or of a different level of education are 52.75% and 26.5% lower, respectively, compared to borrowing between similar managers. Finally, doubling the age difference and the experience difference of the managers reduces the odds of borrowing by 3% and 14.8%, respectively.

11.3 Central Reorganization of Workers Across Lines to Avoid Delays

As mentioned above, Adhvaryu et al. (2021a) show that upper management sometimes preemptively reassigns high-efficiency workers to low productivity lines at the beginning of an order, particularly from important buyers, to lower the chance of missing the order delivery deadline. This leads to a negative assortative matching between workers and managers at the beginning of the order. In these cases, workers are reassigned for a relatively long period of time. In Appendix S, we show that excluding trades that occur in the first week of an order or longer trades, which are more likely to be centrally planned, has little effect on the results.

We begin by showing that the distribution of borrowing spells matches closely the distribution of absenteeism spells of workers in Figure S.1. 40% of absenteeism spells last 1 day, with 65% of them lasting 3 days or less. Similarly, 50% of borrowing spells last for a day and 70% last for 3 days or less. In the left panel of Figure S.2, we show that the average borrowing spell length is around 6 days for trades initiated during the first week of an order; while it falls to 2.5 days for trades initiated after the first week.[123] The right panel shows that about 30% of workers borrowed during the first week of a borrower's order are borrowed for one week or more; while this percentage falls to 8% in subsequent weeks consistent with the evidence shown in Adhvaryu

[123]The average order is 17-18 work days long with the median order lasting more than 14 work days.

et al. (2021a). Moreover, 75% of workers borrowed after the first week of an order are borrowed for 1-2 days; while this is the case for only 40% of trades during the first week.

Next, we count the number of high and low efficiency workers traded from high-efficiency lines to other high-efficiency lines, from low to low-efficiency lines, and between high and low-efficiency lines. When excluding long trades and those initiated in the first week of an order to ignore worker moves most likely to reflect upper-management's preemptive reorganization of workers across lines, Figure S.3 shows that workers are much more likely to flow between lines of similar efficiency levels than they are to flow between lines of differing average efficiency and that flows of high and low efficiency workers are balanced. If these remaining worker moves were still reflecting the NAM pattern identified in Adhvaryu et al. (2021a), we would expect most trades to involve high efficiency workers and to occur between lines of differing efficiency.

In Figure S.4, we reinforce this idea by showing that managers are much more likely to form main partnerships with managers of similar efficiency levels. That is, high (low) efficiency managers are more likely to establish their main partnerships with other high (low) efficiency managers on their floor than they are to form partnerships with managers of differing efficiency. Finally, having established that excluding long trades or those initiated in the first week of an order isolates trades least likely to reflect the preemptive reorganization of production by upper management to avoid missed deadlines for important buyers, we check that our main results are robust to excluding these worker moves. Tables S.1 and S.2 show that the results presented in Table 12 are statistically and qualitatively similar when excluding long spells and moves initiated in the first week of an order, respectively.

Note we do not mean to imply that upper management has no interest or involvement in the absenteeism-induced short-term sharing of workers by way of these relationships. It is of course possible or even likely that upper management encourages managers to help each other with their absenteeism-related worker needs, and that the desire to appear cooperative to upper management might enter the incentive compatibility constraint in some way. The results just indicate that the span of control and/or informational asymmetry problems we mention above are large enough to make central coordination of the redistribution of workers impossible, leaving need for relational contracts to determine cooperation.

11.4 Determinants of Trading Activity

We next investigate if key dimensions of managerial quality shown to be predictive of high productivity lines in Adhvaryu et al. (2021d) are correlated with trading intensity. Note that we include manager fixed effects in the main regression specifications above such that managerial quality does not drive the pair-wise trading patterns shown. However, in addition to the transaction costs modeled and investigated above, managerial traits or practices might determine a particular manager's need for or reliance on trading.

Table 13 shows that managers exhibiting greater Control (i.e., a stronger belief in their own ability to impact performance rather than acquiescing to fate or chance) are more active traders. This pattern is consistent with the results in Adhvaryu et al. (2021d) showing Control to be one of the strongest contributors to line productivity. On the other hand, we also see that managers exhibiting greater Attention are less active traders. This pattern is consistent with a stronger ability to leverage within line worker-task reassignments to mitigate any potential productivity losses as demonstrated in Adhvaryu et al. (2019). That is, if a manager is more able to make do with the workers they have, their need to borrow (and therefore interest in maintaining partnerships through lending) would be subdued.[124]

Table 13: Determinants of Trading Activity

	(1) Number of workers borrowed
Autonomy	-0.0433
	(0.0439)
Control	0.165***
	(0.0390)
Attention	-0.225***
	(0.0531)
log(Days since order started)	0.0343
	(0.0459)
Observations	9494
Mean of Y	48.26
SD	16.30

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress the total daily number of workers borrowed by managers on managerial characteristics and on the log of the number of days since the order started. We include standardized measures of Autonomy, Control, and Attention. We also include unit, year, month, day of the week, and style fixed effects. We cluster the standard errors reported in parentheses at unit by date level.

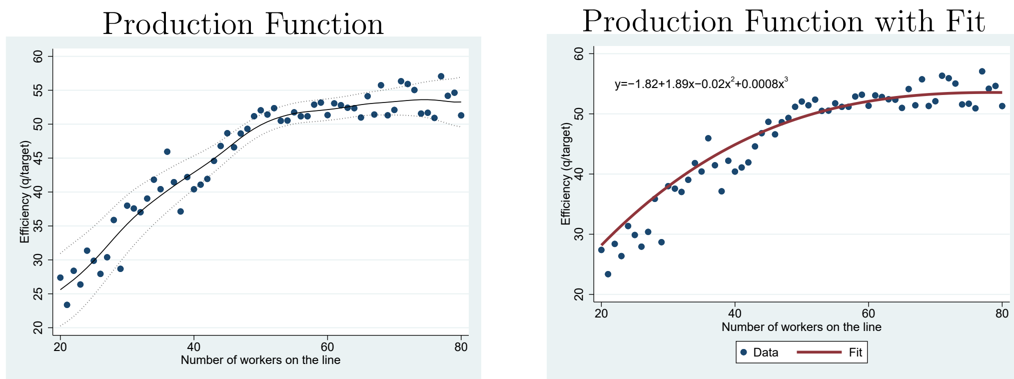
We also include the same learning-by-doing measure used in Adhvaryu et al. (2021d) to check whether an imbalance in length of orders across managers might be driving any observed patterns in trading activity. The small and insignificant coefficient helps to alleviate concerns that learning-by-doing is confounding any of the results. As mentioned above, we also control for this measure in our main specifications.

[124] Adhvaryu et al. (2021d) identify seven factors of managerial quality, but we focus here on those which proved most important for productivity in that analysis. We exclude only Tenure as it is likely correlated with both ability to make do with available workers and age of relationships but would be less clearly interpretable than the pair-wise measure we already use above.

12 Simulations

In this section, we report the results of several counterfactual simulations to study the extent to which firm investments in relationship formation would help solve the worker misallocation problem resulting from idiosyncratic absenteeism realizations across lines. The global garment industry is highly competitive and characterized by low profit margins. From previous work and discussions with the firm we estimate that approximately 5% of the revenues are converted into profits. Further, each percentage point increase in efficiency translates into a 0.1875-0.25 percentage point increase in profit (Adhvaryu et al., 2018). This implies that a one percentage point increase in efficiency represents a 3.75-5% increase in the *profit margin*.

Figure 13: Average efficiency by the number of workers on the line



Note: In the first panel, we plot the average efficiency by the number of workers on the line across managers and the 95% confidence interval for this average. For ease of presentation, we censor the figure at 20 and 80 workers on the line. Less than 5% of observations have fewer than 20 or more than 80 workers on the line. In the second panel, we also estimate a functional form for the relationship between efficiency and the number of workers on the line by regressing daily efficiency on a 3rd degree polynomial in the number of workers on the line and manager, unit, year, month, and day of the week fixed effects. We find the following functional form: efficiency$= -1.82 + 1.89x - 0.02x^2 + 0.0008x^3$ where x is the number of workers on the line. We compute the predicted efficiency given by the polynomial for every manager and days. We plot the average predicted efficiency against the number of workers on the line. The estimation is done over all manager-day observations, but we censor the figure at 20 and 80 workers on the line.

For the simulations that follow, we begin by estimating a reduced-form production function. We first plot efficiency (output) on the number of workers on the production line (input). The first panel of Figure 13 shows that relationship. Consistent with the results in Figure 8, panel (b), this relationship is clearly concave. Efficiency increases sharply until 50-55 workers and is nearly constant afterwards. We then approximate this empirical function by regressing efficiency on a 3rd degree polynomial in the number of workers on the line and on our usual fixed effects. The second panel of Figure 13 shows the average predicted efficiency produced by a 3rd degree polynomial estimate.

The gist of our simulations is as follows. For any given day, we observe the *status quo* equilibrium distribution of worker absenteeism shock realizations as well as lending/borrowing behavior on the part of managers. We then amplify (or restrict) this behavior by increasing (decreasing) the flow of workers across new relationship pairs, further decreasing (increasing) the misallocation of workers across lines. We then use the "production function" estimated above to determine the resulting line productivity and aggregate (plant-day-level) productivity effects.[125] We iterate this procedure for a given number of days to estimate the mean and standard error of the impact estimate. We present the comparisons of the resulting productivities across all simulations in Figure 14 below.

12.1 Benchmarks

We study three scenarios – no redistribution of workers (maximal misallocation); perfect redistribution (no misallocation); and an exogenous reduction in absenteeism.

No redistribution. We begin by asking what the simulated productivity losses are, going from the *status quo* level of redistribution via relationships to a counterfactual scenario in which relational contracts are shut down – i.e., there are no worker transfers across lines. In terms of the model, this simulation is equivalent to increasing transaction costs to a point where any trade is too costly. In this scenario, managers must make do with only present

[125] In all simulations, we assume the production function that is implied by Figure 13. That is, we assume that the relationship between the number of workers on the line and efficiency is approximated by the 3rd degree polynomial displayed in the second panel of Figure 13. We also assume throughout that the production function remains fixed before and after the counterfactual policy change.

home line workers; that is, absenteeism shocks are not smoothed at all, and worker misallocation is maximized.

We start by drawing 100 production days (without replacement) at random. For each day, we compute the predicted efficiency with the current trades by plugging the number of workers on the line into the estimated production function. To compute the scenario without trade, we use only the number of home line workers present in our estimate. The number of home line workers in the unit would be the number of workers on the line if lines did not trade. We repeat this exercise 100 times and compute the mean and standard error across the replications. We find that efficiency falls when trade is shut down entirely by 0.90 percent, from 49.13% (SE 0.004) to 48.69% (SE 0.005), which corresponds to a decrease of 1.65-2.2% in the firm's profit margin.[126]

Optimal redistribution. As a second benchmark, we study productivity under a counterfactual scenario with perfect redistribution of available workers across lines. This represents the first-best (*ex post*) solution for the firm, conditional on the pattern of worker absenteeism realizations observed in the data. In this simulation, we compute the loss (gain) of every line in the unit from losing (gaining) 1 worker. The line with the smallest loss then gives that worker to the line with the largest gain. We repeat that exercise as long as the smallest loss is less than the largest gain.[127] We draw 100 days and perform this procedure on each day; we then repeat this exercise 100 times to compute standard errors around simulated treatment estimates. Predicted productivity is 49.13% (SE 0.004) prior to redistribution and 49.90% (SE 0.007) after. This change represents a 1.58 percent increase in aggregate efficiency, which

[126]All changes in predicted efficiency presented below represent significant differences at the 1% level.

[127]We repeat that exercise for increments of 0.1, 0.01, and 0.001 workers to reflect the fact that workers can be traded for a fraction of a day and fully exploit the gains from trade.

translates to a 2.89-3.85% increase in the profit margin.

Reducing absenteeism by half while shutting down trade. Then, we study a benchmark scenario in which the firm (say, via high-powered incentives) reduces absenteeism on each line by half. Within this scenario, we study the same two sub-cases as above. Let us first consider a case where lines do not trade at all and keep their additional home line workers that are present due to the decrease in absenteeism. We find that the average efficiency increases by 1.08 percent (from 49.13% (SE 0.004) to 49.66% (SE 0.004)) – a 1.99-2.65% increase on the profit margin.

Reducing absenteeism by half plus optimal redistribution. We also consider a case where all workers including the additional workers that are present due to the reduction in absenteeism are optimally traded just like in the optimal redistribution case. We find that the average efficiency increases by 3.43% from 49.13 (SE 0.004) to 50.82% (SE 0.013) translating to a 6.34-8.45% on the profit margin.

12.2 Policy Counterfactuals

In the next two simulations, we investigate the role of physical and identity based distance. We postulated throughout the essay that these distances can affect the transaction cost within pairs of managers in various ways. An example policy that the firm could implement would be to introduce an app in which managers could log the number of workers they need or are willing to spare.[128] Excess workers would then be assigned optimally to the lines most in

[128] The identity of the managers could be anonymous to other managers, but verifiable by upper-level managers in order for the latter to audit the managers and elicit truthful revelations of the need for and excess of workers.

need. Such a tool, if carefully implemented, could eliminate the need for interactions between the managers which would effectively eliminate the negative effect of physical and identity-based distances.

Reducing physical distance plus optimal redistribution. We first investigate how reducing physical distance would affect efficiency. In particular, we ask what would be the effect of reducing the average physical distance to 1 foot assuming that trades are done optimally. From column 3 of Table 12, we find that lines would borrow on average 73.36% more if the distance would fall to 1 foot on average.[129] To compute the effect of decreasing physical distance, we proceed in a similar way as we did previously.

For every day that we draw, we compute the average number of workers borrowed in every unit. Then, we calculate what would be this average if it were to increase by 73.36%. We trade workers optimally until this new average is reached or until there are no gains from trade as we did for the optimal trade policy change in the optimal distribution case. We repeat the exercise 100 times to compute the standard errors. We find that reducing distance would increase efficiency by 1.49% on average (from 49.13% (SE 0.004%) to 49.87% (SE 0.005%)) – a 2.78-3.7% increase in the profit margin.

Reducing demographic distance plus optimal redistribution. Finally, we investigate whether there are gains from reducing demographic distances among the managers. The aim is to reduce gender, education, age and experience differences simultaneously. If we were to use the estimates in Table 12,

[129] All else equal, the predicted number of workers borrowed in pairs 9.37 feet away (the average), is given by $\theta_{ij}^{\bar{D}} = e^{X\beta - 0.2459 \times ln(9.37)} = e^{X\beta} e^{-0.2459 \times ln(9.37)}$. If distance were equal to 1, the predicted number of workers borrowed would be $\theta_{ij}^{1} = e^{X\beta - 0.2459 \times ln(1)} = e^{X\beta}$, where $X\beta$ represent the other variables in the regression. Therefore, all else equal, we would expect the number of workers borrowed to increase by $\frac{e^{X\beta} - e^{X\beta} e^{-0.2459 \times ln(9.37)}}{e^{X\beta} e^{-0.2459 \times ln(9.37)}} = \frac{1 - e^{-0.2459 \times ln(9.37)}}{e^{-0.2459 \times ln(9.37)}}$ =0.7336 or 73.36% on average.

we would ignore the fact that some demographic characteristics may be correlated with one another. To circumvent this problem, we construct a binary variable equal to 1 whenever the managers in a pair have any demographic differences.[130] Then, we estimate the same regression as before except that we use this single binary variable as a measure of demographic difference. The results are presented in Appendix T. Using the estimates in column 3, we find that the number of workers borrowed in dissimilar pairs would increase by 37.64% if demographic differences were eliminated.[131] In our sample, 92.5% of pairs have any demographic differences. Hence, if demographic differences were to be eliminated, we would expect that the average number of workers borrowed would increase by 37.64% for 92.5% of pairs. In other words, we would expect that the daily number of workers borrowed would increase by 37.64%×92.5%=34.82% on average.

To compute the effect of decreasing demographic differences, we proceed in a similar way as before. For every day that we draw, we compute the average number of workers borrowed in every unit. Then, we calculate what would be this average if it were to increase by 34.82%. We trade workers optimally until this new average is reached or until there are no gains from trade. We repeat the exercise 100 times to compute the standard errors. We find that the average efficiency increases by 0.9% from 49.13 (SE 0.004) to 49.58% (SE 0.005), corresponding to a 1.69-2.25% increase in the profit margin.

Figure 14 plots the average efficiency under all simulations on the left y-

[130] More precisely, this variable equals 1 when managers are of different genders, or have a different level of education, or their age difference is above median, or their experience difference is above median.

[131] All else equal, in demographically dissimilar pairs, the predicted borrowing is $\theta^1_{ij} = e^{X\beta-0.3195\times 1} = e^{X\beta}e^{-0.3195}$ and in similar pairs, $\theta^0_{ij} = e^{X\beta-0.3195\times 0} = e^{X\beta}$, where $X\beta$ represent the other variables in the regression. Therefore if dissimilar pairs were to become similar, we would expect trade to increase on average by $\frac{e^{X\beta}-e^{X\beta}e^{-0.3195}}{e^{X\beta}e^{-0.3195}} = \frac{1-e^{-0.3195}}{e^{-0.3195}}$ =0.3764 or 37.64%.

axis and shows above each marker the percentage increase or decrease from the baseline scenario (denoted by the black line).[132] Comparing the no trade scenario to the optimal trade scenario under the observed level of efficiency reveals that trades are left on the table and that the firm would benefit from amplifying trading between the managers. In fact, the current level of trade exploits less than 40% of the potential efficiency gains.[133] While going from no trade to optimal trade increases efficiency by 2.3-2.5%,[134] cutting absenteeism by half has a smaller effect in the range of 1.8-2%.[135] Moreover, the last two simulations reveal that demographic differences and physical distance put large barriers on trade. Indeed, reducing demographic differences and physical distance could allow the firm to exploit 57% and 94% of the gains realized under optimal trading, respectively.

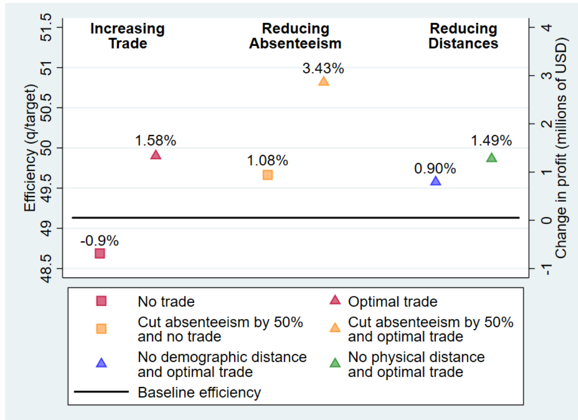
[132] All differences between the point estimates are significant at the 1% level. The 99% confidence bands are smaller than the marker size and are not displayed on the graph.

[133] (base line-no trade)/(optimal trade-no trade)=(49.13-48.69)/(49.9-48.69)=0.364.

[134] Under the curent level of absenteeism, going from the no trade equilibrium to the optimal trade equilibrium increases efficiency by $100 \times \frac{49.9-48.69}{48.69}$ =2.49%. Doing the same when absenteeism falls by half leads to an increase of 2.32%

[135] Going from the current level of absenteeism to the a 50% reduction of absenteeism within the no trade equilibrium increases efficiency by $100 \times \frac{49.66-48.69}{48.69}$ =2.01% and by 1.83% within the optimal trade equilibrium.

Figure 14: Plant-level Gains in Efficiency across Simulations



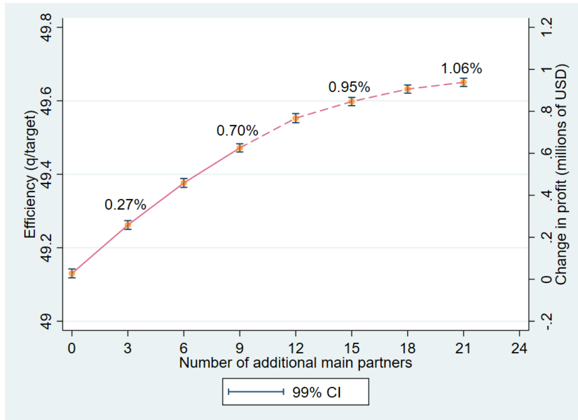
Note: As a baseline, we first compute predicted efficiency given by the data. We then compute the efficiency gain from this baseline when absenteeism remains at its observed level, but managers do not trade (first marker) and when workers are traded optimally (second marker). Then, we compute the efficiency gain when absenteeism falls by half for every line and managers do not trade (third marker), and when workers are traded optimally (fourth marker).Finally we compute the gain in efficiency when workers are traded optimally and demographic distances are eliminated (fifth marker), and when the average physical distance falls to 1 feet (sixth marker).

Finally, we compute back-of-the-envelope profit changes that would result from these changes in misallocation. On the right vertical axis of Figure 14, we plot the increase (or decrease) in profit from baseline for each simulation using the most conservative estimates. We find that if the firm could reach the optimal trading equilibrium, profit would increase by \$1.44 million per year under the current level of absenteeism and by \$3.16 million per year if absenteeism also falls by half. Hence, the results suggest that fostering an environment that promotes partnerships can benefit the firm greatly.

Increasing the number of main partners. We investigate next how valuable are bilateral relationships for the firm. We reproduce our main regression presented in Table 12 and include a dummy variable for whether the partner is one of the manager's 3 main partners. The results are presented in Table T.2 of Appendix T. Using the estimates in column 3, we find that a manager borrows 51% more from his main partners than from other partners. In this exercise, we ask what are the gains to increasing the number of main partners. To do so, we proceed in a similar fashion as we did for the demographic distance simulation. We first increase the number of main partners by 3 for every manager. Hence, in a unit with N lines, a manager would see an increase of its number of workers borrowed by 51% for $100 \times 3/N$ percent of its partners or an increase of $100 \times .51 \times (3/N)$ percent. Since we do the same exercise for all lines in the unit, we would expect the average number of workers borrowed in the factory to increase by that same percentage.

For every day that we draw, we compute the average number of workers borrowed in every unit. Then, we find what would be this average if it were to increase to its new predicted level with 3 additional main partners for every manager. We trade workers optimally until this new average is reached or until there are no gains from trade. We repeat the exercise 100 times to compute the standard errors. We estimate the new efficiency if we add 3 to 21 additional main partners in increments of 3 and present the results in Figure 15.

Figure 15: Plant-level Gains in Efficiency with Additional Main Partners



Note: As a baseline, we first compute predicted efficiency given by the data, with no additional main partners. We then compute the efficiency when we add 3, 6, 9, 12, 15, 18, and 21 additional main partners. We display the percentage increase in efficiency from baseline above the markers. Note that at baseline, every managers have 3 main partners so only N-3 additional main partners can be added, where N is the number of lines in the unit. The smallest unit has 14 lines. Hence, only 11 additional main partners can be added in that unit. On the dashed segment, we add the minimum between x and N-3 main partners, where x is the value on the x-axis. Hence, on this segment, all partners are main partners in at least one unit. At 21 additional main partners, all partners are main partners in all units.

We find that 3 additional main partners increase efficiency by 0.27% and that when all partners are main partners (21 additional main partners on average across all units), efficiency increases by 1.06%; i.e., from 49.13% (SE 0.004) to 49.26% (SE 0.005) and 49.65% (SE 0.004), respectively. These results suggest that if the firm were to increase partnerships to a maximum, it could achieve up to 70% of the efficiency gains possible under the first best scenario where there are no constraints and all workers are traded optimally. (This is an upper bound since the cost of maintaining relationships may not increase linearly in the number of partners.) While it might be challenging to design a system where workers are optimally traded without friction, it may be easier for the firm to encourage partnerships and increase the number of main partners.

If the firm were able to increase the number of main partners by just 3 (or 6) main partners, we estimate that its profit could increase by 247 thousand dollars per year (or 462 thousand dollars). This suggests that overall, relational contracts are highly valuable for the firm.

13 Conclusion

Relational contracts form the basis of much of the theory of organizational economics. They are what enable firms to remain productive in spite of the infeasibility of formal contract specification and enforcement among coworkers. Yet despite this fundamental role, we have little rigorous empirical evidence on the function and importance of relational contracts within real firm settings, particularly among peers within the same level of the organizational hierarchy. Our study aims to fill this gap by leveraging a unique dataset of managers' interactions in a garment manufacturing firm in India. We focus on the role of these interactions in dealing with the key challenge of mitigating the impacts of worker absenteeism. We show that worker absenteeism – particularly large absenteeism shocks – has substantial impacts on team productivity, which is of first-order importance to both managers and the firm. Next we study how managers leverage relationships to lend and borrow workers in a manner consistent with canonical models of relational contracting.

The two key facts to emerge from this analysis are the following. First, while managers are indeed able to smooth some, mostly small, worker absenteeism shocks, they are unable to leverage relationships to smooth larger shocks, resulting in highly imperfect risk sharing. Managers have strong relationships with about two or three primary partners; they transact very sparingly with other managers. This results in many potentially beneficial transfers being left unrealized. Second, managers are significantly more likely to develop relationships with managers who are both physically close (on the factory floor) as well as similar in terms of identity characteristics. This latter analysis suggests that dyad-specific costs of transacting may serve as meaningful barriers to relationship formation and maturity.

Last, we explore counterfactual simulations in which the firm invests in creating additional relationships. We find substantial gains to mature relationship formation. The magnitudes of the productivity effects in this analysis suggest that worker misallocation (conditional on realizations of absenteeism) plays as central a role in determining productivity as does the problem of absenteeism itself. While in these simulations we remain agnostic as to the specific policies that could create more close relationships among managers, our results offer some clues as to potential policy solutions that may be effective. For example, since physical distance is key, a redesign of production lines on factory floors may bring more managers closer together. Similarly, given that identity characteristics are salient, more homogeneous assignment of managers to factory floors might increase the number of mature relationships. Finally, while centralization of assignment of available workers to lines is likely very difficult for reasons discussed earlier in the essay, hiring an intermediary whose job it is to facilitate quick transactions by reducing costs of interacting among managers (or providing a technological solution that achieves the same goal) may also decrease the degree of aggregate misallocation. We leave the assessment of the effectiveness of these policies to future work in this area.

Chapter III

Learning, Selection, and the Misallocation of Households Across Sectors

14 Introduction

Productivity is much lower in developing countries than in developed countries (Bloom et al., 2010a, Hall and Jones, 1999, Syverson, 2011). Hypothesized drivers of this gap have included managerial quality (Bloom and Van Reenen, 2007, Bloom et al., 2013, Adhvaryu et al., 2021d), trade relationships and costs (Adhvaryu et al., 2019, Atkin et al., 2017, Atkin and Donaldson, 2015), and resource misallocation across sectors (Hsieh and Klenow, 2009). While much of this evidence has focused mainly on non-agricultural sectors and larger formal firms, related empirical work has documented that productivity gaps across developed and developing countries are particularly large in the agricultural sector (Gollin et al., 2014, Restuccia et al., 2008). Misallocation of capital and land has also been hypothesized as a driver of this latter pattern (Restuccia and Rogerson, 2013, Restuccia and Santaeulalia-Llopis, 2017, Adamopoulos et al., 2017), along with self-selection of households across sectors (Alvarez-Cuadrado et al., 2019, Lagakos and Waugh, 2013). Recent models of the process of structural transformation have used labor reallocation frictions to explain productivity patterns across agriculture and non-agriculture sectors (Porzio et al., 2020).

In this essay, we aim to build on this prior evidence, asking if misallocation of households across sectors due to information frictions contributes to low productivity in developing countries across both agriculture and non-agricultural sectors. We hypothesize that imperfect information about relative productivity might lead developing country households to select suboptimally across sectors early on in their productive life cycles. Previous studies have modeled selection as a one-off sorting decision across sectors, limiting the ability to document sectoral sorting mistakes along households' productive life cycles. That is, these analyses can document sectoral sorting for a population at a given point in time, but cannot comment on whether this particular sorting decision is optimal for each household. To the degree that households converge to optimal sectoral choices over time as they learn about which sector best suits their skills, a dynamic approach is required to identify: i) for which sector each household ultimately appears best suited, ii) whether and for how long each household participates in an ill-matched sector, and iii) how much their earnings suffer along the way as a result.

We adapt the dynamic sectoral sorting framework in Gibbons et al. (2005) to the developing country household's decision to engage in non-agricultural work. This model of selection in which households learn about their relative productivity across sectors yields a generalized earnings equation with dynamic correlated random coefficients (DCRC). We use an extension of projection-based panel methods (Chamberlain, 1982, 1984, Islam, 1995, Suri, 2011) to estimate the model on the longitudinal Indonesia Family Life Survey (IFLS), which spans more than two decades.[136] We analytically link the interpretation of our structural estimates to the seminal formulation of the Roy (1951) model in Borjas (1987), which allows us to use our estimates to characterize the

[136]The fundamentals of this approach to panel data are reviewed in Crépon and Mairesse (2008). We discuss later when we develop the methodology how we draw from extensions developed in Islam (1995) to allow for dynamics and Suri (2011) to allow for selection on comparative advantage.

nature of sorting in our context as either positive selection, negative selection, or sorting on comparative advantage.

Results show that households sort across sectors on the basis of comparative advantage, consistent with findings from other recent studies (Papageorgiou, 2014, Adamopoulos et al., 2017, Lagakos and Waugh, 2013). We document substantial heterogeneity in the returns to engaging in non-agricultural work. While the average annual return is roughly 3.9 million rupiah (290 USD), the expected returns among households who actually switch in or stay in the non-agricultural sector are 2 to 4 times as large and the returns for households who switch out or stay out are negative.

We also document substantial churning along the sectoral margin, an empirical regularity across most developing countries that only a few papers have studied (Adhvaryu et al., 2020a, Adhvaryu and Nyshadham, 2017, Calderon et al., 2020). Preliminary evidence from the raw data shows that this churning reduces with experience in a sector. That is, a household is less likely to switch the longer they have been in a particular sector, consistent with learning. Structural estimates confirm that the observed churning is at least in part a result of substantial learning and slow convergence such that many households spend substantial amounts of time in a sector which is suboptimal for them. At the start of the sample, roughly 33% of households are misallocated, and these households are earning 64% less on average than they could have if they were properly sorted across sectors. After 14 years, 24% of households (and not necessarily the same households) remain misallocated, sorting on persistently imprecise perceptions of relative productivity.

We recover structural estimates of both the household's latent relative ability across sectors and its evolving perceptions regarding it over time. We document that returns to participating in the non-agricultural sector are higher for households with members exhibiting higher cognitive ability and better physical health as well as more open-mindedness and extraversion. However, the full set of observable covariates still only explains 9% of the variation in returns across sectors, consistent with the observed prevalence and persistence of suboptimal sorting decisions.

Our approach nests several alternative models which can be ruled out. For example, we can estimate a model with comparative advantage but no dynamics as well as a model with neither dynamics nor heterogeneity in relative earnings across sectors. We find that dynamics are important and in fact that the heterogeneity in relative earnings across sectors is only well fit (and substantial) when allowing for dynamics.

We also evaluate alternative interpretations for the dynamic heterogeneity we observe in the data. One advantage of our projection-based approach to estimating the DCRC model is that it can obtain consistent estimates of both the average return and the latent heterogeneity under these alternative interpretations so long as the assumption of sequential exogeneity is preserved. Under these different models, however, the interpretation of the latent heterogeneity and the expected patterns of the estimated dynamics would differ. We evaluate whether land market frictions, saving out of financial constraints, or skill accumulation (i.e., learning by doing) could explain the patterns we observe in the raw data as well as the structural parameters we recover, and find each of these alternative interpretations to be less consistent with our findings than learning about comparative advantage.

Our study contributes to two strands of the literature on the causes of low productivity in developing countries (Bloom et al., 2010a, Hall and Jones, 1999, Syverson, 2011). Several papers have investigated the role of the misallocation of capital and other non-labor inputs (Hsieh and Klenow, 2009, Restuccia and Rogerson, 2013, Adamopoulos et al., 2017). The misallocation of labor across sectors has also been hypothesized when documenting productivity gaps across sectors (Gollin et al., 2014); and frictions in the movement of labor across sectors has been modeled in studies of sectoral sorting and structural transformation (Pulido et al., 2018, Porzio et al., 2020). We expand on this work by quantifying the degree of labor misallocation and identifying information frictions as a cause – leveraging a long panel to document in which sector each household's earnings are maximized and how often they deviate from this optimal sector. In this sense our essay is closest to the recent work by Adamopoulos et al. (2017) showing in China that labor selection reinforces the negative productivity effects of land and capital misallocation across sectors. We complement this work by documenting that labor selection can be imperfect due to information frictions, leading to substantial and costly misallocation of labor as well.[137]

In doing so, we also build on evidence of the sorting of households across sectors (Alvarez-Cuadrado et al., 2019, Lagakos and Waugh, 2013). We find strong evidence that households sort across sectors on the basis of perceived comparative advantage, but extend the approaches in previous papers to assess whether a household's sorting decision is optimal in each period. Static approaches interpret realized sorting as revealed preference; whereas our DCRC model allows for households to have imperfect information and make mistakes

[137]Note that in our study we aim to explicitly cut past aggregate market level frictions by including community by year fixed effects to focus on information frictions at the household level. In this sense, we aim to complement prior evidence on land and capital market frictions. Those may very well still play a role in our setting in addition to the role of household-level information frictions we focus on, but they should not conflate the analysis we undertake, as discussed below, and are not the primary focus of our study.

along the way as a result. This flexibility allows us to fit the observed sectoral churning in the data, common across contexts but often overlooked in empirical analyses of sorting. Our approach also allows us to recover consistent estimates of the average returns, latent heterogeneity, and correlations between current income realizations and future sectoral choices under several alternative interpretations including saving out of financial constraints and skill accumulation, and then to evaluate which of these interpretations is most consistent with the parameter estimates we recover. As mentioned above, we find the results to be most consistent with a learning about comparative advantage interpretation.

Our essay relates to recent work by Hicks et al. (2017) and Pulido et al. (2018), which use our same longitudinal dataset to evaluate relative productivities of workers across sectors. In fact, the model we use is an extension of the fixed effects approach used by Hicks et al. (2017) in which we allow for dynamic correlated random coefficients.[138] Our model nests both the fixed effects approach and a model of sorting on comparative advantage without dynamics. This allows us to test and reject the ability of these simpler frameworks to match the patterns in the data. We are able to validate the importance of information frictions and learning, which are not considered in either of these two studies but which we find leads to substantial misallocation in household sectoral choice.[139]

[138] Note Hicks et al. (2017) also differ from us in that they perform their analysis at the individual level. In keeping with most other studies which focus on farm and non-farm enterprise in developing country contexts, we prefer to perform our analysis at the household level given the difficulty in measuring intrahousehold labor supply and the division of earnings from these enterprises which are very common in our data, but we show robustness of our results to individual level analysis below.

[139] Pulido et al. (2018) structurally estimate a macro model of sectoral sorting with restrictions to mobility across sectors, which like our approach leverages switching histories to better fit the data, but their estimates suggest that households who switch out of the non-farm sector realize income losses. They justify this either by taste or utility-based compensating differentials or with market frictions leading to switchers-out getting "stuck" in the agriculture sector despite greater earning potential in the non-agricultural sector. Our estimates, on the other hand, show for many households earnings are actually maximized

15 Data and Motivation

15.1 IFLS

We use the Indonesian Family Life Survey (IFLS), a longitudinal household survey that began in 1993, with four follow-ups conducted in 1997, 2000, 2007, and 2014 (Strauss et al., 2016). The sample is representative of the 13 provinces that were selected to be included in the first survey wave (corresponding to over 80% of the Indonesian population). The IFLS collected detailed information about a wide array of household and individual characteristics, including basic demographics, educational attainment, physical health, cognitive ability, risk aversion, and most importantly for this essay, sectoral choice and income from various sources. Specifically, the main respondent for each household is asked about the household's ownership of and income from household enterprise (both farm and non-farm), and each household member aged 15 or older is asked to report their individual wage income as well as the sector of their primary and (if applicable) secondary occupation.

We are interested in total annual household income, which we calculate as the sum of profits from non-farm enterprise, profits from farm enterprise (both of which can be negative or positive), and all household members' wage income.[140] After this, we restrict to households with non-missing non-agricultural profits, farm enterprise profits, and wage income in all five waves. This leaves us with 3875 households in a balanced panel sample.

ultimately in the agricultural sector, such that switching out is ultimately optimal, but convergence to this realization is slow due to information frictions. We argue this explanation better fits the bilateral, high-frequency switching which slowly reduces over time observed in the data. We evaluate alternative interpretations including those related to frictions studied by Pulido et al. (2018) and Adamopoulos et al. (2017) in detail below.

[140] Given the importance of this income variable for our analysis, we first drop outliers in each wave (specifically, the top 1% and bottom 1% of the income distribution), which we suspect suffer from reporting errors – a common method for trimming self-reported incomes.

This essay focuses on the household-level decision to exit the agricultural sector. We use the household as our unit of analysis, as other related work does (Alvarez-Cuadrado et al., 2019, Adamopoulos et al., 2017), because ownership of a household enterprise, which is arguably a household-level rather than an individual-level decision, is common in our sample.[141] In household surveys like the IFLS, it can be difficult or even impossible to allocate and value time use of household members across these household enterprises, let alone to divide profits among all members associated with the enterprises. Nevertheless, we demonstrate robustness of our results to individual level analysis below as well.

As our sectoral choice variable of interest, we generate an indicator equal to one for households who either own a non-farm enterprise or have at least one member working in the non-agricultural sector, though we show that our results are robust to variations of this definition (e.g., having more than half of household members working in the non-agricultural sector). Over the five survey waves, between 54% to 60% of households worked in the non-agricultural sector according to this definition (as shown in Table 14).

In Table 14, we also report total annual household income in millions of 2015 Indonesian rupiahs. In 1993, average household income was approximately 9 million rupiahs (around 650 USD), but by 2014, this increased to approximately 24 million.

[141] In 1993, 39% of IFLS households own a farm business, while 34% own a non-farm business (62% own either). In 2014, the percent of households who own any enterprise is roughly the same (59%), though a larger share own non-farm businesses (38%) than farm businesses (32%) by this time.

Table 14: Summary Statistics

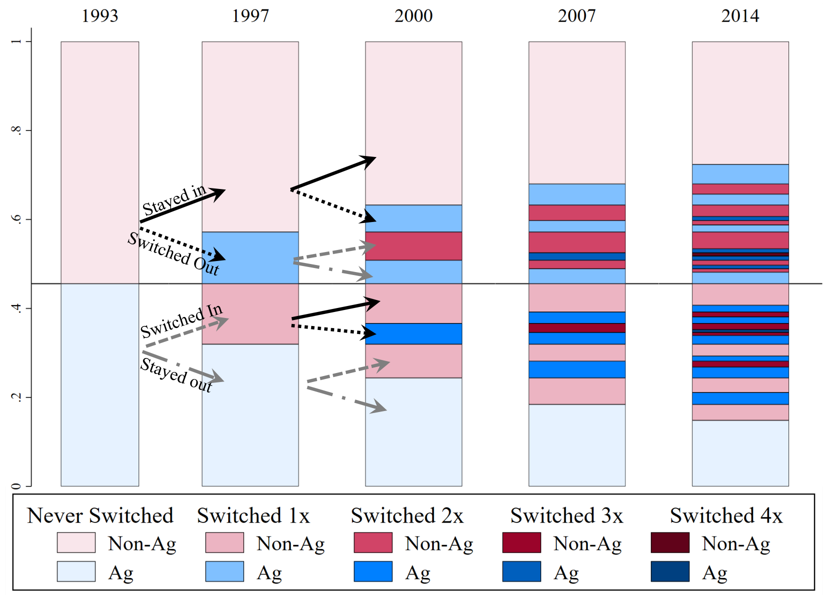
	Year				
	1993	**1997**	**2000**	**2007**	**2014**
Non-Ag Sector	0.54	0.56	0.60	0.60	0.59
	(0.50)	(0.50)	(0.49)	(0.49)	(0.49)
Total Household Income	9.06	11.3	13.5	17.8	23.9
	(13.3)	(14.3)	(16.2)	(21.4)	(31.1)
Household Size	4.69	4.61	4.59	4.14	3.84
	(2.01)	(1.91)	(1.92)	(1.87)	(1.91)
No. Females Aged 15-59	1.38	1.41	1.41	1.33	1.23
	(0.81)	(0.81)	(0.83)	(0.84)	(0.86)
No. Males Aged 15-59	1.27	1.27	1.31	1.26	1.11
	(0.88)	(0.89)	(0.92)	(0.94)	(0.93)
Observations	3875	3875	3875	3875	3875

Notes: Sample consists of IFLS households with non-missing income information in all five waves of the IFLS. Standard deviations reported in parentheses.

15.2 Preliminary Evidence

Basic descriptive exercises reveal substantial churning in and out of agriculture. In Figure 16, we illustrate the share of households in the agricultural and non-agricultural sectors, with five shades of red that represent non-agricultural households and five shades of blue that represent agricultural households. The darkness of a color indicates the number of times a household has switched. In 1993, when we do not have any previous information on sector, all households have never switched according to our data and are therefore represented by the lightest shades of red (for those currently in the non-agricultural sector) and blue (for those currently in agriculture). In 1997, however, close to 20% of the households who were in the non-agricultural sector in 1993 switched to agriculture in 1997 (represented by a slightly darker shade of blue because they switched once). At the same time, around 30% of the 1993 agricultural households switched into non-agricultural work in 1997 (represented by a slightly darker shade of red).

Figure 16: Churning Across Sectors Over Time

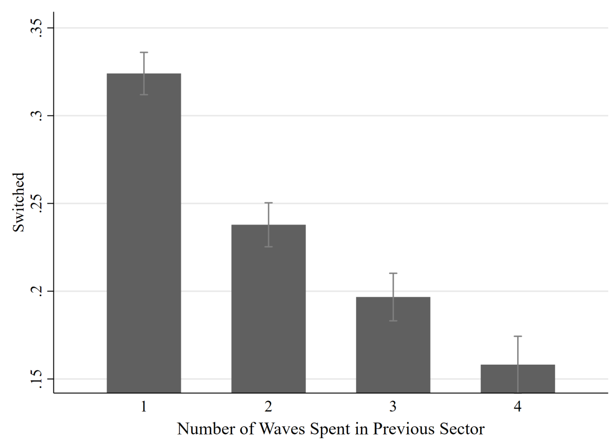


Notes: Sample consists of IFLS households with non-missing income information in all five waves of the IFLS. Shades of red represent households that are in the non-agricultural sector in the relevant wave, while shades of blue represent households that are not. Color darkness captures the number of times a household has switched prior to that wave.

This switching behavior continues across the remaining 3 waves. By 2014, it is clear that over half of households have switched at least once (any color that is not the lightest red or blue represents a household that has switched). There are many households that have switched more than once, and even some that have switched four times. In short, switching sectors is common.

We next ask whether switching declines with the amount of time a household spends in a sector. Figure 17 shows that it does. Among households that have been in their current sector for only one wave (starting from when we first observe them in 1993), over 30% of households switched sectors. This share drops with the cumulative number of waves spent in the previous sector: only about 16% of households who have remained in their sector for 4 waves switch in the fifth wave. This suggests that, though sectoral switching is common, households' switching decisions appear to exhibit convergence, such that longer time spent in a given sector yields a lower probability of switching. In the appendix, we show this pattern holds in both directions (i.e., for both agricultural and non-agricultural households (see Figure X.1)). The patterns depicted in these figures motivate the model we develop in the next section, where workers learn about their sector-specific ability over time. The high-frequency, bidirectional switching and trend of reduced switching over time are also consistent with the stylized facts that motivate the model in Papageorgiou (2014), where workers also learn about their comparative advantage over time.

Figure 17: Switching by Number of Waves Spent in Previous Sector



Notes: Sample consists of IFLS households with non-missing income information in all five waves of the IFLS. Error bars denote 95% confidence intervals.

16 Model

16.1 Sectoral Choice

In this section, we outline a Roy (1951) model of sectoral choice, where household i in period t chooses whether to go into the non-agricultural sector (denoted by superscript N) or stay in the agricultural sector (denoted by superscript A). Sector-specific income Y_{it} is determined by the following equations:

$$\begin{aligned} Y_{it}^N &= \beta_t^N + \eta_i^N \\ Y_{it}^A &= \beta_t^A + \eta_i^A. \end{aligned} \tag{17}$$

β_t^N is average income in the non-agricultural sector and β_t^A is average income in the agricultural sector. η_i^N is the unobserved, heterogeneous component of productivity specific to the non-agricultural sector, while η_i^A is the corresponding component for the agricultural sector.

We can rewrite both η_i^N and η_i^A as a function of relative productivity $(\eta_i^N - \eta_i^A)$, and absolute advantage, τ_i, which we define as the component of the household-specific productivity that has the same effect on the household's productivity in both sectors. (Accordingly, τ_i does not affect the sectoral choice.) Specifically, we rewrite each sector-specific productivity term in the following way:

$$\eta_i^N = (1+\phi)\eta_i + \tau_i$$
$$\eta_i^A = \eta_i + \tau_i, \tag{18}$$

where both ϕ and η_i depend on projection coefficients, b_A and b_N.[142] We define $\phi \equiv b_N/b_A - 1$, and $\eta_i \equiv b_A(\eta_i^N - \eta_i^A)$.

The equations in (18) show that a household's sector-specific productivity is a function of both relative productivity and absolute advantage. Importantly, the parameter ϕ depends on the covariance between non-agricultural and agricultural productivity in the population as a whole, $Cov(\eta_i^N, \eta_i^A)$, and therefore summarizes the nature of sorting in the population.

To explore how ϕ governs the nature of selection in the Roy model, we combine equations (17) and (18) and suppress t subscripts to express income in the non-agricultural and agricultural sectors as follows:

$$Y_i^N = \beta^N + (1+\phi)\eta_i + \tau_i$$
$$Y_i^A = \beta^A + \eta_i + \tau_i.$$

Unconditional expected income (in the non-agricultural and agricultural sec-

[142]Since with 2 sectors only the relative magnitude of η_i^A and η_i^N can be identified, we will define, following Lemieux (1998) and Suri (2011), η_i^A and η_i^N in terms of the household's relative productivity in non-agricultural over agricultural activity $(\eta_i^N - \eta_i^A)$ using the following projections: $\eta_i^A = b_A(\eta_i^N - \eta_i^A) + \tau_i$ and $\eta_i^N = b_N(\eta_i^N - \eta_i^A) + \tau_i$, where $b_N = (\sigma_N^2 - \sigma_{NA})/(\sigma_N^2 + \sigma_A^2 - 2\sigma_{NA})$, $b_A = (\sigma_{NA} - \sigma_A^2)/(\sigma_N^2 + \sigma_A^2 - 2\sigma_{NA})$, with $\sigma_{NA} \equiv Cov(\eta_i^N, \eta_i^A)$, $\sigma_N^2 \equiv Var(\eta_i^N)$, and $\sigma_A^2 \equiv Var(\eta_i^A)$.

tor) is

$$E[Y_i^N] = \beta^N + (1+\phi)E[\eta_i] + E[\tau_i]$$
$$E[Y_i^A] = \beta^A + E[\eta_i] + E[\tau_i].$$

Let D_i represent a dummy equal to one for households in the non-agricultural sector. Households sort across sectors based on their η_i; specifically, households with $\phi\eta_i > -\beta$ (where $\beta \equiv \beta^N - \beta^A$) will choose to go into non-agricultural work ($D_i = 1$). Therefore, conditional average non-agricultural and agricultural income, among those who select into the non-agricultural sector, is the following:

$$\begin{aligned}
E[Y_i^N|D_i = 1] &= E[Y_i^N|\phi\eta_i > -\beta] \\
&= \beta_t^N + (1+\phi)E[\eta_i|\phi\eta_i > -\beta] + E[\tau_i|\phi\eta_i > -\beta] \\
&= \beta_t^N + (1+\phi)E[\eta_i|\phi\eta_i > -\beta] + E[\tau_i] \\
E[Y_i^A|D_i = 1] &= E[Y_i^A|\phi\eta_i > -\beta] \\
&= \beta_t^A + E[\eta_i|\phi\eta_i > -\beta] + E[\tau_i|\phi\eta_i > -\beta] \\
&= \beta_t^A + E[\eta_i|\phi\eta_i > -\beta] + E[\tau_i],
\end{aligned}$$

where the last step is due to the independence of τ and η.

We focus on the same income differentials as Borjas (1987), who characterizes sorting by distinguishing between positive selection, negative selection, and "refugee sorting" or sorting on comparative advantage. The first differential of interest is the difference between average non-agricultural income among households that select into the non-agricultural sector and unconditional average non-agricultural income (labeled Q_1 in Borjas (1987) and defined by equation (19) below). The second differential of interest is the difference between average agricultural income among households that select into the non-agricultural sector and unconditional average agricultural income (labeled Q_0 in Borjas (1987) and defined by equation (20) below). Positive selection is defined as the case when $Q_1 > 0$ and $Q_0 > 0$, negative selection when $Q_1 < 0$ and $Q_0 < 0$, and sorting on comparative advantage when $Q_1 > 0$ and $Q_0 < 0$.

$$E[Y_i^N|D_i = 1] - E[Y_i^N] = (1 + \phi)\left(E[\eta_i|\phi\eta_i > -\beta] - E[\eta_i]\right) \tag{19}$$

$$E[Y_i^A|D_i = 1] - E[Y_i^A] = \left(E[\eta_i|\phi\eta_i > -\beta] - E[\eta_i]\right). \tag{20}$$

16.1.1 Case 1: $\phi > 0$

When $\phi > 0$, average non-agricultural income among those who select into the non-agricultural sector is higher than the population average of non-agricultural income, as shown below. Average agricultural income is also higher among those who select into the non-agricultural sector. This means that non-agriculture households are positively selected.

$$E[Y_i^N|D_i = 1] - E[Y_i^N] = \overbrace{(1 + \phi)}^{>0}\overbrace{\left(E[\eta_i|\eta_i > -\frac{\beta}{\phi}] - E[\eta_i]\right)}^{>0} > 0$$

$$E[Y_i^A|D_i = 1] - E[Y_i^A] = \overbrace{\left(E[\eta_i|\eta_i > -\frac{\beta}{\phi}] - E[\eta_i]\right)}^{>0} > 0.$$

16.1.2 Case 2: $-1 < \phi < 0$

When $-1 < \phi < 0$, we have negative selection. Both average non-agricultural income and average agricultural income among those who select into the non-agricultural sector are lower than population averages. Those who select into the non-agricultural sector tend to be less productive in both sectors.

$$E[Y_i^N|D_i = 1] - E[Y_i^N] = \overbrace{(1+\phi)}^{>0}\overbrace{\left(E[\eta_i|\eta_i < -\frac{\beta}{\phi}] - E[\eta_i]\right)}^{<0} < 0$$
$$E[Y_i^A|D_i = 1] - E[Y_i^A] = \overbrace{\left(E[\eta_i|\eta_i < -\frac{\beta}{\phi}] - E[\eta_i]\right)}^{<0} < 0.$$

16.1.3 Case 3: $\phi < -1$

Finally, when $\phi < -1$, average non-agricultural income among those who select into the non-agricultural sector is higher than the population average of non-agricultural income. However, average agricultural income is lower among those who select into the non-agricultural sector. This implies sorting based on comparative advantage: productive non-agricultural households would have low productivity in agriculture, while productive agricultural households would have low productivity in the non-agricultural sector.

$$E[Y_i^N|D_i = 1] - E[Y_i^N] = \overbrace{(1+\phi)}^{<0}\overbrace{\left(E[\eta_i|\eta_i < -\frac{\beta}{\phi}] - E[\eta_i]\right)}^{<0} > 0$$
$$E[Y_i^A|D_i = 1] - E[Y_i^A] = \overbrace{\left(E[\eta_i|\eta_i < -\frac{\beta}{\phi}] - E[\eta_i]\right)}^{<0} < 0.$$

16.1.4 Generalized Income Equation

Reintroducing t subscripts and combining equations (17) and (18), we arrive at the following generalized income equation:

$$Y_{it} = \alpha_t + \beta D_{it} + \eta_i(1 + \phi D_{it}) + \tau_i, \tag{21}$$

where $\alpha_t \equiv \beta_t^A$ and $\beta \equiv (\beta_t^N - \beta_t^A)$, which we assume to be constant over time.[143] Estimation of the parameters β and ϕ is complicated by the fact that D_{it} is endogenous. As described above, households will choose $D_{it} = 1$ if they expect higher earnings in the non-agricultural sector (that is, if $\phi\eta_i > -\beta$) .

16.2 Learning

Having established that households make their sorting decision based on η_i, we now discuss what households know about their own η_i, and how this knowledge evolves over time. We assume that households know the population average earning in both sectors (α_t, β), their own absolute advantage (τ_i), and ϕ, but have imperfect information about their comparative advantage (η_i).[144] In particular, we introduce an additive productivity shock, ε_{it}, to η_i in equation (21) and assume that $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2 = 1/h_\varepsilon)$. That is, the household only observes the sum of η_i and ε_{it}, but not either individually. The generalized

[143] As we discuss later, when we estimate the model we will explicitly purge all outcome variables and regressors of variation in means across communities and within communities over time, using community fixed effects that vary across time periods (essentially, community-by-time dummies). These fixed effects will account for changes in relative output prices across sectors, as long as relative prices do not vary within a community in a single year. Under these conditions, extending the analysis to estimate a time-varying β seems of little empirical benefit.

[144] As we explain below, ϕ can be thought of as the value of skills in each sector, where the skills are captured by the comparative advantage component.

income equation then becomes:

$$Y_{it} = \alpha_t + \beta D_{it} + (\eta_i + \varepsilon_{it})(1 + \phi D_{it}) + \tau_i \tag{22}$$

Households hold the initial belief that $\eta_i \sim N(m_{i0}, \sigma^2 = 1/h)$; and this belief is refined each period using output observations, Y_{it}. That is, from Y_{it}, households can compute

$$l_{it} = \frac{Y_{it} - \alpha_t - \beta D_{it} - \tau_i}{(1 + \phi D_{it})} = \eta_i + \varepsilon_{it}, \tag{23}$$

a noisy signal of their relative productivity η_i, which is independent of their period t sectoral choice. Let $l_i^t = (l_{i1}, ..., l_{it})$ denote the history of household i's normalized relative productivity observations through period t. Then, the posterior distribution of η_i given history l_i^t is distributed $N(m_t(l_i^t), 1/h_t)$, where

$$m_t(l_i^t) = \frac{hm_{i0} + h_\varepsilon(l_{i1} + ... + l_{it})}{h + th_\varepsilon}, \qquad \text{and} \qquad h_t = h + th_\varepsilon \tag{24}$$

Note that the specific learning mechanism proposed here allows households to learn about returns to participating in the non-agricultural sector each period, irrespective of the sector the household has chosen that period. This learning structure is borrowed from Gibbons et al. (2005) who use it to study learning about comparative advantage in a model of occupational choice.[145] The bidirectional churning and convergence observed in the raw data motivates the use of this approach in our setting (see Figures 16 and X.1).

The intuition behind this proposed mechanism is that relative productivity, η_i, is an index of fundamental skills which affect productivity in both sectors,

[145] They, in turn, borrow heavily from the classic development in DeGroot (1970). Please see these previous works for more in depth discussion of this framework.

but is valued differentially across the two sectors. Assuming that the household knows ϕ but not η_i corresponds to assuming the household knows how much each sector values these skills but not their own skill stock. Accordingly, households can learn about their stock through production in either sector.

For example, suppose that η_i represents the household's managerial skill and that while both sectors reward this skill, the non-agricultural sector rewards it more heavily. The assumptions of the model imply that the household recognizes that the non-agricultural sector rewards managerial ability more than the agricultural sector does; however, the household is unsure of its specific stock of managerial skill.

Of course, an excellent manager might still be able to earn more in the agricultural sector than someone with worse managerial skill (but who is similar in other ways). Therefore, a household that initially believes it is bad at management will operate in the agricultural sector to start, where this lack of managerial skill is less penalized; however, should this household find this period that it is better able to manage its agricultural inputs (for example) than it expected, it will decide to enter the non-agricultural sector next period, knowing that this would be lucrative for a household with strong managerial ability. The mechanism, of course, works in the opposite direction as well. We should note that, to the degree that both sectors reward some skills (e.g., work ethic) *equally*, these skills are represented by τ_i and will affect household income in both sectors, but will not affect the return to switching sectors.

Household i will choose the non-agricultural sector in period t if $E[Y_{it}^N - Y_{it}^A] > 0$, and choose the agricultural sector otherwise. That is, household i will choose the non-agricultural sector in period t (i.e., $D_{it} = 1$) if and only if $\phi m_i^{t-1} > -\beta$.

16.3 Estimation

Allowing for measurement error in equation (22), our estimating equation is the following:

$$Y_{it} = \alpha_t + \beta D_{it} + (\eta_i + \varepsilon_{it})(1 + \phi D_{it}) + \tau_i + \zeta_{it} \tag{25}$$

where measurement error ζ_{it} is assumed mean independent of sector and input decisions conditional on η_i and τ_i. That is, in particular, we will assume $E(D_{it}|\zeta_{it}, \eta_i, \tau_i) = E(D_{it}|\eta_i, \tau_i)$.

As discussed above, D_{it} will depend on the mean of the household's prior distribution on η_i coming into period t, $m_{i,t-1}$, which we cannot observe. Accordingly, OLS estimates of β will be biased. We now develop a strategy which allows us to consistently estimate β, recover ϕ, and validate the importance of learning dynamics in this empirical context.

In particular, in order to recover consistent estimates of β, we must purge the composite unobserved term, $(\eta_i + \varepsilon_{it})(1 + \phi D_{it}) + \tau_i + \zeta_{it}$, of its correlation with D_{it}. We know from section 16.2 that the portion of $(\eta_i + \varepsilon_{it})$ which correlates with sectoral choices is $m_{i,t-1}$. We will begin by decomposing $m_{i,t-1}$ into two components which have distinct effects on the household's history of sectoral choices. Note that the Bayesian updating of beliefs implies that the mean of the prior distribution is a martingale. That is, the law of motion for $m_{i,t}$ is

$$m_{i,t} = m_{i,t-1} + \xi_{it} \quad \Rightarrow \quad m_{i,t-1} = m_{i0} + \sum_{k=1}^{t-1} \xi_{ik}, \tag{26}$$

where ξ_{it} is a noise term orthogonal to $m_{i,t-1}$. Then, denoting $\tilde{m}_{i,t-1} \equiv$

$\sum_{k=1}^{t-1} \xi_{ik}$ as the sum of the signals received up to period $t-1$, we have

$$Y_{it} = \alpha_t + \beta D_{it} + (m_{i0} + \tilde{m}_{i,t-1} + \omega_{it})(1 + \phi D_{it}) + \upsilon_{it}, \tag{27}$$

where $\upsilon_{it} \equiv \tau_i + \zeta_{it}$ is orthogonal to sectoral choice in period t, D_{it}, by construction and $\omega_{it} \equiv \eta_i + \varepsilon_{it} - (m_{i0} + \tilde{m}_{i,t-1})$ is orthogonal to D_{it} by nature of the martingale structure of $m_{i,t-1}$.

Extending the approaches developed by Chamberlain (1982, 1984), Islam (1995), and Suri (2011), we can overcome the endogeneity of D_{it} by projecting m_{i0} and $\tilde{m}_{i,t-1}$ onto the history of sectoral choices. In particular, the law of motion of the prior, as expressed in equation (26), suggests that the initial belief, m_{i0}, will affect sectoral choices in all periods. On the other hand, the cumulative update, $\tilde{m}_{i,t-1}$, will only affect sectoral choices in period t onwards.

We have five waves of data and therefore four cumulative updates. The projection of the initial belief, m_{i0}, which appears in the estimating equation for all periods, will include the entire history of sectoral choices as follows:[146]

$$m_{i0} = \lambda_0 + \prod_{k=1}^{5}(1 + \lambda_k D_{ik}) - 1 + \psi_{i0} \tag{28}$$

where ψ_{it} is projection error in period t. The projection of each cumulative

[146] If we expand m_0, we get: $m_0 = \lambda_0 + \lambda_1 D_1 + \lambda_2 D_2 + \lambda_3 D_3 + \lambda_4 D_4 + \lambda_5 D_5 + \lambda_{12} D_1 D_2 + \lambda_{13} D_1 D_3 + \lambda_{14} D_1 D_4 + \lambda_{15} D_1 D_5 + \lambda_{23} D_2 D_3 + \lambda_{24} D_2 D_4 + \lambda_{25} D_2 D_5 + \lambda_{34} D_3 D_4 + \lambda_{35} D_3 D_5 + \lambda_{45} D_4 D_5 + \lambda_{123} D_1 D_2 D_3 + \lambda_{124} D_1 D_2 D_4 + \lambda_{125} D_1 D_2 D_5 + \lambda_{134} D_1 D_3 D_4 + \lambda_{135} D_1 D_3 D_5 + \lambda_{145} D_1 D_4 D_5 + \lambda_{234} D_2 D_3 D_4 + \lambda_{235} D_2 D_3 D_5 + \lambda_{245} D_2 D_4 D_5 + \lambda_{345} D_3 D_4 D_5 + \lambda_{1234} D_1 D_2 D_3 D_4 + \lambda_{1235} D_1 D_2 D_3 D_5 + \lambda_{1245} D_1 D_2 D_4 D_5 + \lambda_{1345} D_1 D_3 D_4 D_5 + \lambda_{2345} D_2 D_3 D_4 D_5 + \lambda_{12345} D_1 D_2 D_3 D_4 D_5 + \psi_{i0}$, where $\lambda_{ijklm} = \lambda_i \lambda_j \lambda_k \lambda_l \lambda_m$.

update, $\tilde{m}_{it}$, includes only the sectoral choices in $t+1$ and onward:

$$\begin{aligned}
\tilde{m}_{i1} &= \theta_{20} + \theta_{22} D_{i2} + \theta_{23} D_{i3} + \theta_{24} D_{i4} + \theta_{25} D_{i5} + \psi_{i1} \\
\tilde{m}_{i2} &= \theta_{30} + \theta_{33} D_{i3} + \theta_{34} D_{i4} + \theta_{35} D_{i5} + \psi_{i2} \\
\tilde{m}_{i3} &= \theta_{40} + \theta_{44} D_{i4} + \theta_{45} D_{i5} + \psi_{i3} \\
\tilde{m}_{i4} &= \theta_{50} + \theta_{55} D_{i5} + \psi_{i4}. \qquad (29)
\end{aligned}$$

Note that the martingale structure of the prior on η_i implies that learning is *efficient*; that is, all information the household will use to make its decision at time t is fully summarized in the initial condition m_{i0} and the sum of the orthogonal updates to period $t-1$, $\tilde{m}_{i,t-1}$. In other words, the path by which the prior reaches $m_{i,t-1}$ will not, conditional on $m_{i,t-1}$ itself, affect sectoral choice in period t, D_{it}. Most importantly, the path by which the sum of the updates reaches $\tilde{m}_{i,t-1}$ will not, conditional on both the initial belief m_{i0} and $\tilde{m}_{i,t-1}$ itself, affect D_{it}. Therefore, we need not include past sectoral choices nor the interactions of future sectoral choices in the update projections in (29).

Note also that the relative sizes of h and h_ϵ will determine the degree to which the initial condition, m_{i0}, or subsequent updates, $\tilde{m}_{i,t-1}$, correlate more strongly with choices across periods. We do not explicitly discuss this relationship further as the estimation will approach this issue agnostically. That is, the estimation will allow the data to show (in the projection coefficients) the degree to which initial conditions and subsequent updates affect choices without restricting *a priori* the relative magnitudes of these correlations. If, for example, a large dispersion in the initial conditions effectively makes their impact on production decisions negligible, the coefficients in equation (28) will be estimated as indistinguishable from 0, while those from the equations in (29) might be estimated with larger magnitudes and more precision.

Plugging projections (28) and (29) into equation (27), and grouping terms, we can now express each Y_t as a function of all sectoral choices as shown below.[147]

$$
\begin{aligned}
Y_{i1} =& \alpha_1 + \beta D_{i1} + (\lambda_0 + \prod_{t=1}^{5}(1+\lambda_t D_{it}) - 1)(1+\phi D_{i1}) + \\
& (\omega_{i1} + \psi_{i0})(1+\phi D_{i1}) + \nu_{i1} \\
Y_{i2} =& \alpha_2 + \beta D_{i2} + (\lambda_0 + \prod_{t=1}^{5}(1+\lambda_t D_{it}) - 1 + \theta_{20} + \sum_{t=2}^{5}\theta_{2t} D_{it})(1+\phi D_{i2}) + \\
& (\omega_{i2} + \psi_{i0} + \psi_{i1})(1+\phi D_{i2}) + \nu_{i2} \\
Y_{i3} =& \alpha_3 + \beta D_{i3} + (\lambda_0 + \prod_{t=1}^{5}(1+\lambda_t D_{it}) - 1 + \theta_{30} + \sum_{t=3}^{5}\theta_{3t} D_{it})(1+\phi D_{i3}) + \\
& (\omega_{i3} + \psi_{i0} + \psi_{i1} + \psi_{i2})(1+\phi D_{i3}) + \nu_{i3} \\
Y_{i4} =& \alpha_4 + \beta D_{i4} + (\lambda_0 + \prod_{t=1}^{5}(1+\lambda_t D_{it}) - 1 + \theta_{40} + \sum_{t=4}^{5}\theta_{4t} D_{it})(1+\phi D_{i4}) + \\
& (\omega_{i4} + \psi_{i0} + \psi_{i1} + \psi_{i2} + \psi_{i3})(1+\phi D_{i4}) + \nu_{i4} \\
Y_{i5} =& \alpha_5 + \beta D_{i5} + (\lambda_0 + \prod_{t=1}^{5}(1+\lambda_t D_{it}) - 1 + \theta_{50} + \theta_{55} D_{i5})(1+\phi D_{i5}) + \\
& (\omega_{i5} + \psi_{i0} + \psi_{i1} + \psi_{i2} + \psi_{i3} + \psi_{i4})(1+\phi D_{i5}) + \nu_{i5}
\end{aligned} \tag{30}
$$

This results in the following reduced form regressions, where income in each period depends on all five D_{it} as well as their double, triple, quadruple, and quintuple interactions:

[147] It is important that we properly specify the projections in (28) and (29). That is, we must include all necessary elements of the history of sectoral choices in order to ensure that the projection errors (ψ) are, indeed, orthogonal to current choices.

$$Y_{it} \quad = \gamma_0^t + \prod_{k=1}^{5}(1+\gamma_k^t D_{ik}) - 1 + \nu_{it}. \tag{31}$$

If we define $\gamma_{ijklm}^t \equiv \gamma_i^t \gamma_j^t \gamma_k^t \gamma_l^t \gamma_m^t$, each equation has 32 reduced form coefficients to be estimated.[148] Following Chamberlain (1982, 1984), we will first estimate these reduced form coefficients by seemingly unrelated regressions (SUR) and then estimate from these coefficients the structural parameters of the model using minimum distance. After normalizing each of the intercepts in equations (28), (29), and (31),[149] there are 43 structural parameters of the model (31 λ coefficients, 10 θ coefficients, β, and ϕ), to be identified from the 155 reduced form coefficients using the minimum distance restrictions implied by the model. The minimum distance restrictions are reported in Appendix section Y.1.

For simplicity, we have not included any covariates in the exposition above, although one could argue that there are household-level characteristics which are correlated with household income and also sectoral choice D_{it}. Though the inclusion of covariates will affect reduced form expressions (31), it will not

[148]Expanding, we obtain: $Y_{it} = \gamma_0^t + \gamma_1^t D_1 + \gamma_2^t D_2 + \gamma_3^t D_3 + \gamma_4^t D_4 + \gamma_5^t D_5 + \gamma_{12}^t D_1 D_2 + \gamma_{13}^t D_1 D_3 + \gamma_{14}^t D_1 D_4 + \gamma_{15}^t D_1 D_5 + \gamma_{23}^t D_2 D_3 + \gamma_{24}^t D_2 D_4 + \gamma_{25}^t D_2 D_5 + \gamma_{34}^t D_3 D_4 + \gamma_{35}^t D_3 D_5 + \gamma_{45}^t D_4 D_5 + \gamma_{123}^t D_1 D_2 D_3 + \gamma_{124}^t D_1 D_2 D_4 + \gamma_{125}^t D_1 D_2 D_5 + \gamma_{134}^t D_1 D_3 D_4 + \gamma_{135}^t D_1 D_3 D_5 + \gamma_{145}^t D_1 D_4 D_5 + \gamma_{234}^t D_2 D_3 D_4 + \gamma_{235}^t D_2 D_3 D_5 + \gamma_{245}^t D_2 D_4 D_5 + \gamma_{345}^t D_3 D_4 D_5 + \gamma_{1234}^t D_1 D_2 D_3 D_4 + \gamma_{1235}^t D_1 D_2 D_3 D_5 + \gamma_{1245}^t D_1 D_2 D_4 D_5 + \gamma_{1345}^t D_1 D_3 D_4 D_5 + \gamma_{2345}^t D_2 D_3 D_4 D_5 + \gamma_{12345}^t D_1 D_2 D_3 D_4 D_5 + \psi_{i0}$, where $\gamma_{ijklm}^t = \gamma_i^t \gamma_j^t \gamma_k^t \gamma_l^t \gamma_m^t$.

[149]We normalize the intercepts such that the estimates of the projection coefficients are mean zero, as follows:

$$\begin{aligned}
\lambda_0 &= 1 - \prod_{t=1}^{5}(1+\lambda_t \bar{D}_t) \\
\theta_{20} &= -\theta_{22}\bar{D}_2 - \theta_{23}\bar{D}_3 - \theta_{24}\bar{D}_4 - \theta_{25}\bar{D}_5 \\
\theta_{30} &= -\theta_{33}\bar{D}_3 - \theta_{34}\bar{D}_4 - \theta_{35}\bar{D}_5 \\
\theta_{40} &= -\theta_{44}\bar{D}_4 - \theta_{45}\bar{D}_5 \\
\theta_{50} &= -\theta_{55}\bar{D}_5,
\end{aligned}$$

where $\bar{D}_t$ is the sample mean of the non-agricultural dummy in period t. An analogous exercise is conducted for the reduced form regressions in (31).

affect the relationships between the reduced form coefficients on the choices and the structural parameters of interest. We control for community fixed effects and household composition variables (number of household members, number of women aged 15-59, and number of men aged 15-59) in each equation of the first stage SUR estimation. Note that by allowing each community effect to vary across waves, we are also able to account for local community-level demand shocks and price fluctuations that may affect switching decisions but do not convey any information about household-level perceptions of relative ability across sectors.

16.4 Identification

16.4.1 Identifying Assumptions

We obtain estimates of the structural parameters through the minimum distance restrictions, which map 43 structural parameters to 155 reduced form coefficients. When we plug in all of the projections into the generalized earnings equation to create equation (30), it can be seen that, in each period, the unobservable error term includes the product of D_{it} and $\omega_{it} + \sum_{k=0}^{t-1} \psi_{ik}$. We therefore must assume that $(\omega_{i1} + \psi_{i0})$ is uncorrelated with D_{i1}, $(\omega_{i2} + \psi_{i0} + \psi_{i1})$ is uncorrelated with D_{i2}, and so on.

Given that the ψ_{it} terms are the projection error terms in (29), they are orthogonal to the relevant sectoral choice indicators by construction. However, we also require that the other component, $\omega_{it} \equiv \eta_i + \varepsilon_{it} - (m_{i0} + \tilde{m}_{i,t-1})$, is orthogonal to D_{it}. Recall that ε_{it} represents the productivity shock in period t. We are therefore assuming sequential exogeneity of the current period's productivity shock. Productivity shocks in a given period are allowed to influence decisions in future periods (as households use them to update their beliefs about η_i), but decisions in a given period cannot be influenced by productivity shocks in future periods. If households can predict future productivity shocks (e.g., good rains next year, infrastructure expansion in the village in the near future, rising demand for a specific good in village) and respond to them in their sector decisions, the update projection, as specified, will not fully account for the endogeneity in these choices. (Note, however, that these future predictions only matter if they are household-specific because community by time fixed effects are projected off in the first stage.) Specifically, there are no λ's and θ's included in the estimation to capture correlations between future idiosyncratic shocks and past household sectoral choices. These correlations are assumed to be zero in order to be able to identify the model with multiple endogenous choices and a small number of periods. Specifically, relaxing this assumption further in a model with heterogeneous returns would make the model not fully identified.[150]

In our theoretical model, the main source of endogeneity in the generalized income equation (22) is the fact that households sort into sectors based on their η_i and learn about their η_i over time. However, the empirical strategy outlined above will recover consistent estimates of β and ϕ under alternative models, as long as they satisfy sequential exogeneity. Suppose, for example, that households do not learn about their η_i over time, but need to save in order to overcome entry or switching costs before they can change sectors. Alternatively, households might not learn about their η_i over time but instead might be able to change their η_i through skill accumulation, as would be

[150]Though this essay contributes to the literature on panel data estimators of correlated random coefficients models by relaxing the strict exogeneity assumption to sequential exogeneity to allow for dynamics, we leave it to future work to relax the sequential exogeneity assumption further to allow for correlations of regressors with both past and future shocks.

the case in a learning by doing model. In both of these examples, as long as sequential exogeneity holds, we can still recover consistent estimates of β and ϕ. However, estimates of θ (which govern how dynamics in relative earning potential η_i relate to future sectoral choices), along with the descriptive evidence from Figures 16 and 17, will allow us to detect whether one of these alternative models appears to be more plausible. We discuss this in more detail in section 17.5.

16.4.2 Identification Intuition

Identification of the structural parameters, such as β, ϕ, the λ's and θ's, comes from a comparison of the income trajectories across households with different sectoral choice histories. That is, we observe in the data the conditional sample mean of income for each sector choice history in each period (i.e. $E(Y_{it}|D_{i1}, D_{i2}, D_{i3}, D_{i4}, D_{i5})$). The econometric strategy uses variation in these means, as well as their evolution over time, across households with different sectoral histories, to recover the structural parameters of interest.

To help clarify the intuition behind the identification, we consider the simplified two-period version of the model described above. The generalized income equations are:

$$Y_{i1} = \alpha_1 + \beta D_{i1} + (m_{i0} + \omega_{i1})(1 + \phi D_{i1}) + v_{i1}$$
$$Y_{i2} = \alpha_2 + \beta D_{i2} + (m_{i0} + \tilde{m}_{i,1} + \omega_{i2})(1 + \phi D_{i2}) + v_{i2}.$$

The projections are then:

$$m_{i0} = \lambda_0 + \prod_{k=1}^{2}(1 - \lambda_k D_{ik}) - 1 + \psi_{i0}$$

$$m_{i0} = \lambda_0 + \lambda_1 D_{i1} + \lambda_2 D_{i2} + \lambda_1 \lambda_2 D_{i1} D_{i2} + \psi_{i0}$$

$$m_{i0} = \lambda_0 + \lambda_1 D_{i1} + \lambda_2 D_{i2} + \lambda_{12} D_{i1} D_{i2} + \psi_{i0}$$

$$\tilde{m}_{i1} = \theta_{20} + \theta_{22} D_{i2} + \psi_{i1}. \tag{32}$$

Replacing the projections in the income equations and grouping terms allows us to obtain the following reduced form equations:

$$\begin{aligned}
Y_{i1} =& \alpha_1 + \beta D_{i1} + (\lambda_0 + \lambda_1 D_{i1} + \lambda_2 D_{i2} + \lambda_{12} D_{i1} D_{i2} + \psi_{i0} + \omega_{i1})(1 + \phi D_{i1}) + v_{i1} \\
Y_{i1} =& \overbrace{\alpha_1 + \lambda_0}^{\gamma_0^1} + \overbrace{[\beta + (1+\phi)\lambda_1 + \lambda_0 \phi]}^{\gamma_1^1} D_{i1} + \overbrace{[\lambda_2]}^{\gamma_2^1} D_{i2} + \overbrace{[(1+\phi)\lambda_{12} + \lambda_2 \phi]}^{\gamma_{12}^1} D_{i1} D_{i2} \\
&+ \underbrace{(\psi_{i0} + \omega_{i1})}_{\perp D_{i1}} \phi D_{i1} + \underbrace{\psi_{i0} + \omega_{i1} + v_{i1}}_{u_{i1}} \\
Y_{i1} =& \gamma_0^1 + \gamma_1^1 D_{i1} + \gamma_2^1 D_{i2} + \gamma_{12}^1 D_{i1} D_{i2} + u_{i1}
\end{aligned} \tag{33}$$

$$\begin{aligned}
Y_{i2} =& \alpha_2 + \beta D_{i2} + \\
& (\lambda_0 + \lambda_1 D_{i1} + \lambda_2 D_{i2} + \lambda_{12} D_{i1} D_{i2} + \psi_{i0} + \theta_{20} + \theta_{22} D_{i2} + \psi_{i1} + \omega_{i2})(1 + \phi D_{i2}) + v_{i2} \\
Y_{i2} =& \overbrace{\alpha_2 + \lambda_0 + \theta_{20}}^{\gamma_0^2} + \overbrace{[\lambda_1]}^{\gamma_1^2} D_{i1} + \overbrace{[\beta + (1+\phi)(\lambda_2 + \theta_{22}) + \phi(\lambda_0 + \theta_{20})]}^{\gamma_2^2} D_{i2} + \\
& \underbrace{[(1+\phi)\lambda_{12} + \lambda_1 \phi]}_{\gamma_{12}^2} D_{i1} D_{i2} + \underbrace{(\psi_{i0} + \psi_{i1} + \omega_{i2})}_{\perp D_{i2}} \phi D_{i2} + \underbrace{\psi_{i0} + \psi_{i1} + \omega_{i2} + v_{i2}}_{u_{i2}} \\
Y_{i2} =& \gamma_0^2 + \gamma_1^2 D_{i1} + \gamma_2^2 D_{i2} + \gamma_{12}^2 D_{i1} D_{i2} + u_{i2}.
\end{aligned} \tag{34}$$

These reduced form coefficients (γ's) represent differences in income between four different groups of households: those that stay in the non-agricultural sector in both periods ($D_{i1} = 1, D_{i2} = 1$), stay out of the non-agricultural sector in both periods ($D_{i1} = 0, D_{i2} = 0$), switch into the non-agricultural sector in period 2 ($D_{i1} = 0, D_{i2} = 1$), and switch out of the non-agricultural sector in period 2 ($D_{i1} = 1, D_{i2} = 0$). Specifically, it can be shown that

$$
\begin{aligned}
\gamma_1^1 =& E(Y_{i1}|D_{i1} = 1, D_{i2} = 0) - E(Y_{i1}|D_{i1} = 0, D_{i2} = 0) \\
\gamma_2^1 =& E(Y_{i1}|D_{i1} = 0, D_{i2} = 1) - E(Y_{i1}|D_{i1} = 0, D_{i2} = 0) \\
\gamma_{12}^1 =& E(Y_{i1}|D_{i1} = 1, D_{i2} = 1) - E(Y_{i1}|D_{i1} = 1, D_{i2} = 0) \\
& - [E(Y_{i1}|D_{i1} = 0, D_{i2} = 1) - E(Y_{i1}|D_{i1} = 0, D_{i2} = 0)] \\
\gamma_1^2 =& E(Y_{i2}|D_{i1} = 1, D_{i2} = 0) - E(Y_{i2}|D_{i1} = 0, D_{i2} = 0) \\
\gamma_2^2 =& E(Y_{i2}|D_{i1} = 0, D_{i2} = 1) - E(Y_{i2}|D_{i1} = 0, D_{i2} = 0) \\
\gamma_{12}^2 =& E(Y_{i2}|D_{i1} = 1, D_{i2} = 1) - E(Y_{i2}|D_{i1} = 1, D_{i2} = 0) \\
& - [E(Y_{i2}|D_{i1} = 0, D_{i2=1}) - E(Y_{i2}|D_{i1} = 0, D_{i2} = 0)] .
\end{aligned} \tag{35}
$$

As with the 5-period version of the model, equations (33) and (34) are estimated by a seemingly unrelated regression which allows us to recover estimates for the γ coefficients. We then estimate the structural parameters through minimum distance where the minimum distance restrictions are as follows.[151]

[151] Although it appears that there are 8 structural parameters to be estimated from 6 equations, we impose the following normalizations:

$$
\begin{aligned}
\lambda_0 &= -\lambda_1 \overline{D_{i1}} - \lambda_2 \overline{D_{i2}} - \lambda_{12} \overline{D_{i1} D_{i2}} \\
\theta_0 &= -\theta_2 \overline{D_{i2}} \quad ,
\end{aligned}
$$

where $\overline{D_{ij}}$ is the average sectoral decision in period j and $\overline{D_{i1} D_{i2}}$ is the average of the

$$\begin{aligned}
\gamma_1^1 &= \beta + (1+\phi)\lambda_1 + \lambda_0\phi \\
\gamma_2^1 &= \lambda_2 \\
\gamma_{12}^1 &= (1+\phi)\lambda_{12} + \lambda_2\phi \\
\gamma_1^2 &= \lambda_1 \\
\gamma_2^2 &= \beta + (1+\phi)(\lambda_2+\theta_{22}) + \phi(\lambda_0+\theta_{20}) \\
\gamma_{12}^2 &= (1+\phi)\lambda_{12} + \lambda_1\phi. \qquad (36)
\end{aligned}$$

The minimum distance restrictions show how β, ϕ, the λ's, and the θ's are recovered from the reduced form (γ) coefficients in equations (33) and (34). For example, the average return to non-agricultural work (β) is identified by the minimum distance restrictions for γ_1^1 (the difference in period 1 income between those who switch out and those who stay out) and γ_2^2 (the difference in period 2 income between those who switch in and those who stay out). Note that γ_1^1 and γ_2^2 are not solely determined by β. For instance, a large positive γ_1^1 could be due to a large positive β or a large positive $(1+\phi)\lambda_1$. Because λ_1 represents the difference in m_{i0} between those who switch out and those who stay out (see equation (32)), the latter could result from positive selection ($\phi > 0$), which would lead to the switch-out households (who are in the non-agricultural sector in period 1) having higher η_i than the stay-out households (who are in the agricultural sector in period 1) and therefore a positive $(1+\phi)\lambda_1$. Alternatively, selection based on comparative advantage ($\phi < -1$) would lead to the switch-out households having lower η_i than the

interaction between the sectoral decisions in periods 1 and 2. These normalizations will make estimates of the projection coefficients mean zero and reduce the number of projection coefficients to be estimated by 2, improving efficiency at no real loss of generality or interpretation.

stay-out households ($\lambda_1 < 0$) and once again a positive $(1 + \phi)\lambda_1$.

To illustrate the intuition behind how ϕ is identified, we conduct three simulations using different values of ϕ (but the same values for β and the same distribution of η_i), shutting down the learning mechanism to focus on the identification of ϕ. For each simulation, we calculate the average income for each of the four groups described above (stay in, stay out, switch in, and switch out) in each period and plot the trajectory of average income, expressed as a deviation from the period-specific mean, for each of the four groups. In Figure 18, panel A illustrates the case of positive selection ($\phi > 0$), panel B illustrates negative selection ($-1 < \phi < 0$), and panel C illustrates sorting based on comparative advantage ($\phi < -1$). All panels assume a positive return to the non-agricultural sector (β).

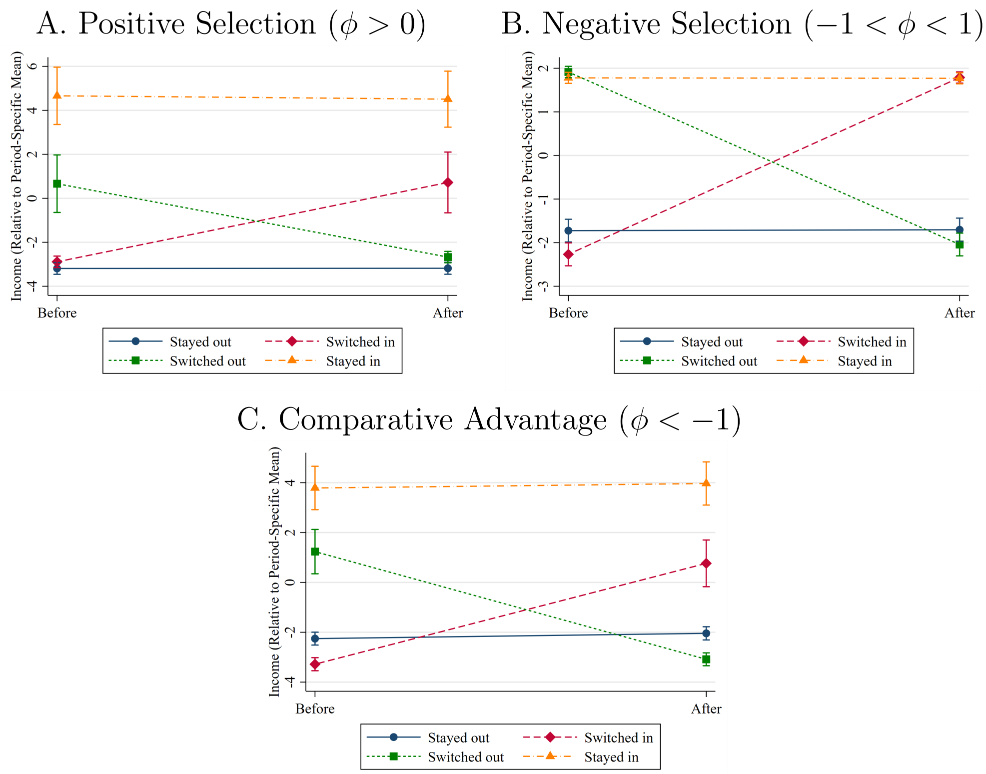
Figure 18 demonstrates that different values of ϕ imply different patterns of income trajectories and income differences across the four groups. In panel A, when there is positive selection, those who stay in (yellow triangles) have higher period 1 income than those who switch out (green squares). This is because those who switch out are more marginal and have lower η_i on average. On the other hand, when there is negative selection (in panel B), those who switch out have (slightly) higher period 1 income than those who stay in. This is because negative selection implies that those with lower η_i are more likely to enter the non-agricultural sector, which means that the more marginal households (who switch out) should have higher η_i on average (and under negative selection the coefficient on η_i in the generalized income equation is positive for households in the non-agricultural sector). Finally, in panel C, we also see that those who switch out have lower period 1 income than those who stay in, similar to the case of positive selection. Under sorting based on comparative advantage, those with low η_i choose the non-agricultural sector, which means the more marginal switch-out households have higher η_i. Because $\phi < 1$, however, the coefficient on η_i is negative for those who are in the non-agricultural sector, which leads to higher income among the stay-in households that have lower η_i.

It is also important to compare the period 1 income of those who switch in (red diamonds) and those who stay out (blue circles). Under positive selection, those who switch in have higher period 1 income than those who stay out because they have higher η_i. Under negative selection and comparative advantage, the opposite is true, for reasons similar to those outlined in the previous paragraph.

Differences in period 2 income also contribute to the identification of ϕ. For example, comparing the period 2 income of those who switch in with those who stay in, we see in Panel A that period 2 income of the stay in group is higher. This is because those who stay in must have higher η_i on average than those who are more marginal and therefore switch in later. In panel B, these two groups have almost identical period 2 income, though that of the switch in group (who are more marginal and therefore have higher η_i under negative selection) is slightly higher. In panel C, period 2 income for those who switch in is lower than for those who stay in: those who switch in are more marginal and therefore have higher η_i on average under comparative advantage sorting, which translates into lower income due to $\phi < -1$. Similar reasoning can explain why period 2 income is higher for those who switch out than for those who stay out under positive selection, while the opposite is true under negative selection and comparative advantage.[152]

[152]There are several group comparisons that cannot be signed solely based on the nature of the sorting process. For example, in panel A, positive ϕ does not necessarily determine

Figure 18: Income by Switch Status, Simulations



Notes: "Stayed out" includes households in agriculture in both period 1 and 2. "Switched In" includes households in agriculture in period 1 and the non-agricultural sector in period 2. "Switched Out" includes households in the non-agricultural sector in period 1 and agriculture in period 2. "Stayed In" includes households in the non-agricultural sector in both periods. Error bars denote 95% confidence intervals. We use $\beta = 4$ and a normally distributed η with mean 0 and standard deviation 3 for all cases, $\phi = 5$ for positive selection, $\phi = -0.9$ for negative selection, and $\phi = -5$ for selection based on comparative advantage.

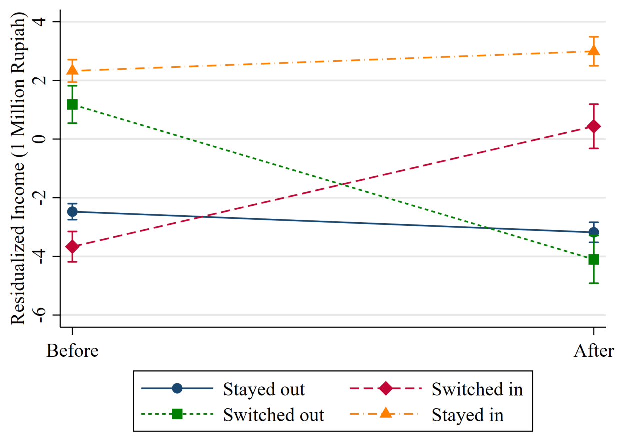
To present some preliminary analysis and preview what we find, we generate a version of Figure 18 that uses our actual data. Specifically, in Figure 19, we plot the evolution of realized incomes, after projecting off community-by-year fixed effects and household composition controls, for four groups of households: period t non-agricultural households who stay in the non-agricultural sector in $t+1$, period t non-agricultural households who switch to agriculture in $t+1$, period t agricultural households who switch into the non-agricultural sector in $t+1$, and period t agricultural households who stay in agriculture in $t+1$. To generate this figure, we include all transitions between waves (such that each household appears multiple times, potentially in different groups), and calculate average residualized income across all households in each group, in the "before" period (t) and the "after" period ($t+1$). The patterns in the data are similar to those documented in panel C of Figure 18, the case of comparative advantage. As we discuss below, our estimated ϕ is indeed consistent with sorting based on comparative advantage, once dynamics are allowed as in our preferred DCRC model.

The minimum distance restrictions in the two-period case (36) also shed light on the identification of the λ and θ coefficients. For instance, two of the λ coefficients are simply equal to the reduced form coefficients γ_2^1 and γ_1^2. That is, the difference in m_{i0} across those who switch out and those who stay out (λ_2) is equal to the difference in period 1 income across those two groups (γ_2^1). Similarly, the difference in m_{i0} for those who switch in and those who stay out (λ_1) is equal to the period 2 income difference across those two groups (γ_1^2).

The learning coefficient is identified by the minimum distance restriction

whether the income differences between switch-out and switch-in households should be positive or negative in either period, but the specific values used in this simulation lead to the switch-out households having higher income in period 1 but lower income in period 2. The comparisons highlighted above, however, are what help identify ϕ.

Figure 19: Income by Switch Status, Data



Notes: Residualized income is calculated by taking the residuals of wave-by-wave regressions of income on community fixed effects and household composition controls. This figure treats each household transition as a separate observation, which means that each household has four observations (one for each transition: 1993-1997, 1997-2000, 2000-2007, and 2007-2014). "Stayed out" includes households in agriculture in both t and $t + 1$. "Switched In" includes households in agriculture in t and the non-agricultural sector in $t + 1$. "Switched Out" includes households in the non-agricultural sector in t and agriculture in $t + 1$. "Stayed In" includes households in the non-agricultural sector in both t and $t + 1$. Error bars denote 95% confidence intervals.

for γ_2^2 (the fifth equation in (36)), which captures the difference in period 2 income between those who switch in and those who stay out. The period 2 income of these two groups differs for several reasons. First, there is an average income gap between the non-agricultural and agricultural sectors (β). In addition, there are underlying differences in η_i across the two groups because those who switch in are closer to the sectoral choice cutoff. These differences in η_i imply there are differences in the m_{i0} (captured by the λ's) and differences in the learning update $\tilde{m}_{i1}$ (captured by the θ's), and the latter component is what informs us about the the learning process. If the magnitude of γ_2^2 is not equal to what we would predict based only on β and the underlying differences in m_{i0} (i.e., $\beta + (1+\phi)\lambda_2 + \phi\lambda_0$), this indicates that the relationship between latent heterogeneity in relative earnings and future sectoral choices is dynamic and the discrepancy generates our estimates of the θ coefficients.

While it is obviously more difficult to demonstrate the precise variation that identifies each of the structural coefficients in the 5-period model, the intuition remains the same: the coefficients are identified by comparing the income trajectories of households with different switching behavior.

16.5 Nested Models

The model described above is a DCRC model that allows for heterogeneous returns to the non-agricultural sector and dynamic relationships between income innovations in the current period and future sectoral sorting decisions. In addition to estimating this preferred model, we also estimate nested models which impose additional restrictions on the relationships between η_i and the endogenous choices, D_{it}. Specifically, we estimate a correlated random coefficients (CRC) model of heterogeneous returns to the non-agricultural sector with static relationships between income innovations and sectoral choices (i.e., strict exogeneity) and a simple fixed effects model with homogeneous returns and no dynamics, which is equivalent to a correlated random effects (CRE) model.

16.5.1 Heterogeneous Returns with Perfect Information: CRC

In the CRC model, households are assumed to have perfect information about their relative productivity η_i, which means there is no longer an additive productivity shock, ε_{it}, nor any updating of expectations about η_i. With perfect information, the model becomes a static CRC model. Models of this sort have been used to study agricultural technology adoption (Suri, 2011) and returns to schooling (Heckman and Vytlacil, 1998).

The estimating equation is nearly the same as in the DCRC model:

$$Y_{it} = \alpha_t + \beta D_{it} + \eta_i(1 + \phi D_{it}) + v_{it}.$$

However, now the household is assumed to have perfect information about its relative productivity, η_i; hence, there is no longer an additive productivity shock, ε_{it}. Therefore, the relationship between η_i and the history of sectoral choices is static. Note, however, that v_{it} could still include exogenous, transitory shocks that shift households from period to period above and below the cutoff for non-agricultural entry. That is, households will sort into a particular sectoral choice history on the basis of η_i and their expectations of Y_{it}^A and Y_{it}^N; however, these expectations will not evolve over time as they do in the imperfect information case.

Accordingly, we need only a single projection in which we project η_i onto the sectoral choice dummies and all of their interactions, as in equation (28):

$$\eta_i = \lambda_0 + \prod_{k=1}^{5}(1 + \lambda_k D_{ik}) - 1 + \psi_{i0}.$$

Because households no longer update their expectations over time, the cumulative updates $\tilde{m}_{it}$ are irrelevant, which means that the θ coefficients in equation (29) are all equal to zero. The CRC model is therefore a restricted version of the DCRC model where all θ coefficients are assumed to be zero. This model has 33 (instead of 43) structural parameters that we estimate from 155 reduced form coefficients (γ) using minimum distance.

16.5.2 Homogeneous Returns with Perfect Information: CRE

In the CRE model, in addition to perfect information about η_i, households are assumed to have homogeneous returns. Because a household's return to the non-agricultural sector no longer depends on their relative productivity η_i, ϕ is assumed to be zero. This amounts to assuming that the data generating process is a simple household fixed effects or CRE model. Under these assumptions, the estimating equation becomes

$$Y_{it} = \alpha_t + \beta D_{it} + \eta_i + v_{it}.$$

We now need only a single projection of η_i on the five sectoral choice dummies:

$$\eta_i \quad = \quad \lambda_0 + \lambda_1 D_{i1} + \lambda_2 D_{i2} + \lambda_3 D_{i3} + \lambda_4 D_{i4} + \lambda_5 D_{i5} + \psi_{i0}.$$

Note that we have not included the interactions of sectoral choice dummies across periods. This is because, once we assume that η_i has no effect on the return to the non-agricultural sector, the changes in choices over time will no longer depend on the initial belief, though the choice in each period still will. As in the CRC model above, all θ coefficients are assumed to be equal to zero. Therefore, the CRE model is a restricted version of the DCRC model where ϕ, all θ coefficients in equation (29), and all λ coefficients in equation (31) – except for λ_1, λ_2, λ_3, λ_4, λ_5 – are assumed to be zero. This model has 5 structural parameters which we estimate from 25 reduced form parameters using minimum distance.

In the existing literature, several studies identify the returns to a particular sector using sector switchers or households that participate in both sectors at once (Herrendorf and Schoellman, 2018, Hicks et al., 2017, Alvarez-Cuadrado et al., 2019, Alvarez, 2020). The assumed data generating process underlying these identification strategies is similar to the CRE model, in which all switchers have the same return. The CRC model relaxes this assumption by allowing heterogeneous returns across households, where households of the same type (defined by a sequence of sectoral choices) have the same type-specific return. Finally, the DCRC model that we use goes a step further and allows the relationship between type and returns to evolve over time.

17 Results

17.1 Structural Minimum Distance Estimates

In Table 15, we present the minimum distance estimates of β and ϕ. The first column displays estimates from our preferred DCRC model. We estimate an average return to the non-agricultural sector (β) of approximately 3.9 million rupiah, which is more than half of the average household income in 1993. ϕ is estimated to be -4.67. Significantly less than 1, this estimate implies that households sort based on comparative advantage in this context, consistent with the patterns shown in Figure 19. That is, households productive in the non-agricultural sector tend to be less productive in agriculture and vice versa.

We next compare our preferred estimates of β and ϕ to those from the two nested models: the CRC model of heterogeneous returns and perfect information, and the CRE model of homogeneous returns and perfect information. Both restricted models substantially over-estimate the average return to the non-agricultural sector. Both the CRC (column 2) and CRE model (column 3) estimate a return of approximately 5 million rupiah.[153] While the CRE model assumes ϕ to be equal to zero, the CRC model does not yield a precisely estimated ϕ: the estimate is positive and statistically insignificant. Neither is consistent with the patterns in the data shown in Figure 19, when referencing the simulations in Figure 18.

In short, ignoring heterogeneity in returns and dynamics results in an overestimation of the average return to the non-agricultural sector and the inability to capture the extent to which households sort based on comparative advantage. Notably, in the DCRC model, ϕ is significantly less than zero, while it is forced to be zero in the CRC model and imprecisely estimated (and positive) in the CRC model. It is clear that the additional flexibility of the DCRC is needed in order to better fit patterns in the data shown in Figure 19.

[153] β^{CRC} and β^{CRE} are statistically significantly larger than β^{DCRC} (p-values are 0.006 and 0.0148 respectively).

Table 15: Structural Estimates

	Specification		
	(1)	(2)	(3)
	DCRC	CRC	CRE
β	3.91***	5.12***	4.96***
	(0.40)	(0.28)	(0.27)
ϕ	-4.67***	17.31	
	(1.75)	(25.60)	

Notes: Structural parameters estimated using minimum distance. Standard errors reported in parentheses. * p< 0.1 ** p< 0.05 *** p< 0.01.. Column 1 reports estimates from the full DCRC model (with heterogeneous returns and imperfect information), column 2 reports estimates from the CRC model (with heterogeneous returns and perfect information), and column 3 reports estimates from the CRE model (with homogeneous returns and perfect information).

17.2 Robustness Checks

Our main conclusions are robust to different definitions of the non-agricultural dummy variable, as we show in Appendix Table X.1. In the first column we report again our baseline estimates, which are based on a non-agricultural dummy variable that equals 1 if a household owns a non-agricultural enterprise or has at least one household member working outside of the agricultural sector. In column 2, we define non-agricultural households as those with a non-agricultural enterprise or more than half of the household working outside the agricultural sector. In column 3, non-agricultural households include those which own a non-agricultural enterprise or earn more than half of their income from non-agricultural wage work. Across all columns, β is positive and ϕ is less than one.

In the last column of Appendix Table X.1, we repeat our analysis using the individual-level dataset used in Hicks et al. (2017), which also relies on the IFLS. We restrict to individuals with non-missing earnings and sector data throughout the first four waves of the panel, use log earnings as our outcome variable, and define our non-agricultural dummy variable to be equal to 1 for individuals whose primary or secondary occupation is non-agricultural.[154] Using this individual-level dataset, we arrive at the same conclusions: the returns to non-agricultural work are positive, and individuals sort across sectors based on comparative advantage.[155]

17.3 Expected Returns

We next examine how sorting and switching behavior is governed by a household's expected returns to participating in the non-agricultural sector. The ability to recover and interpret these patterns is, perhaps, the main strength of our empirical approach. Other approaches to recovering β and even ϕ would not allow for the recovery of each household's expected returns at each decision point, or an analysis of whether these expectations correspond to subsequent choices in ways consistent with the intuition of the model.[156]

First, we calculate $\beta + \phi m_{it}$ for each household, for periods $t = 1$ to 4. This represents a household's expected return to the non-agricultural sector, based on what they have learned up until the end of period t about their relative productivity η_i. In Figure 20, we average these returns for households

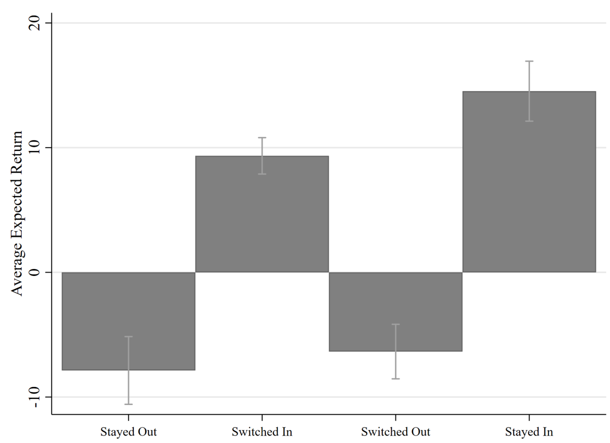
[154] We only use four waves because in the five-wave dataset, there were a few sectoral choice histories that were not experienced by anyone in the dataset (for example, the sequence involving switching in every period), which meant that some coefficients in the SUR could not be estimated.

[155] Note that the magnitudes of our household-level and individual-level β's cannot be compared because the household specifications use income in levels – due to the presence of negative business profits – while the individual specification uses log income, as is done in Hicks et al. (2017).

[156] Though approaches to estimating DCRC models are quite limited in the literature, instrumental variables approaches, for example, used to estimate CRC models (Heckman and Vytlacil, 1998) would not recover these additional parameters. Even to estimate static heterogeneous returns, it would likely be infeasible to find a rich enough set of instruments across such a large set of household types over such a long panel. That is, one would need instruments that predict switching in both directions across households with different relative abilities across different waves just to recover β and ϕ even in the absence of dynamics. For example, price fluctuations alone would not, in general, be enough.

in four different groups: those who stay out of the non-agricultural sector in the next period, those who switch in to the non-agricultural sector, those who switch out of the non-agricultural sector, and those who stay in the non-agricultural sector. As expected, returns to the non-agricultural sector are higher for households in agriculture who switch into the non-agricultural sector compared to those who stay out. Returns are also higher for non-agricultural households who stay in the non-agricultural sector compared to those who switch out. Figure X.2 in the appendix calculates these returns by wave, and separately for current non-agricultural households and current agricultural households – both groups show similar patterns, consistent with both the patterns in the raw data and the learning structure assumed in the model.

Figure 20: Expected Returns by Switch Status



Notes: The figure reports the average return to the non-agricultural sector $(\beta + \phi m_{it})$ across $t = 1$ to 4 and all households in each category. "Stayed out" includes households in agriculture in both t and $t + 1$. "Switched In" includes households in agriculture in t and the non-agricultural sector in $t + 1$. "Switched Out" includes households in the non-agricultural sector in t and agriculture in $t + 1$. "Stayed In" includes households in the non-agricultural sector in both t and $t + 1$. Error bars denote 95% confidence intervals. Standard errors are calculated analytically (see Appendix Y.2).

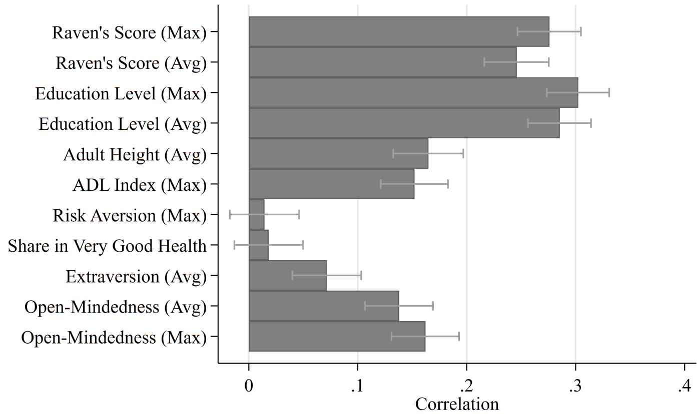
In short, the expected returns estimated by the model are consistent with households' sorting behavior. Note that though the results are fully consistent with the model intuition, the estimated pattern is not mechanical. The estimation strategy does not restrict in any way these recovered correlations between income evolutions and the sequence of choices. For example, we could have found that only households that stayed in expected large gains while households that switched in expected substantially smaller or negligible gains, suggesting that productivity in the new sector accrues over time as in the case of learning by doing (Foster and Rosenzweig, 1995), an alternative model we discuss in more detail in section 17.5. As such, we interpret the internally consistent pattern of estimates here as a resounding confirmation of the intuition of the model and structure assumed.

Using these estimated returns, we next explore what types of households tend to have high returns to the non-agricultural sector. To do this, we take each household's final return ($\beta+m_{i4}$) – which is the household's most informed or precise estimate of its return – and calculate its correlation with various household-level characteristics. We take these household characteristics from the 2014 wave of the IFLS because $\beta + m_{i4}$ is a household's perceived return going into this last wave and because this wave includes variables not found in the others (like personality traits). We first use LASSO to select predictors of final returns from a large set of household-level characteristics covering a wide range of areas: cognitive ability, educational attainment, physical health, risk aversion, mental health, and personality traits (see Appendix section Z.1 for a description of all variables). Then, for each of the eleven variables that were selected, we calculate its correlation with the estimated final return.

These correlations, reported in Figure 21, are statistically significant, and for the most part, have the expected signs.[157] Returns to the non-agricultural

[157] In a multivariate regression that includes all selected variables, however, only Raven's scores (maximum), education (maximum and average), adult height (average), and risk

Figure 21: Expected Returns and Household Characteristics



Notes: Each bar illustrates the correlation between the listed household level characteristic, taken from the 2014 wave of the IFLS, and the final return to the non-agricultural sector ($\beta + m_{i4}$). Error bars denote 95% confidence intervals. These variables were selected from a larger set of variables (listed in Appendix Z.1) using lasso.

sector are positively correlated with cognitive ability (measured by Raven's test scores), educational attainment, height, physical health, open-mindedness, and extraversion. Although the correlation between risk aversion and returns is positive, in a multivariate regression that includes all selected variables, the coefficient on risk aversion is negative (and statistically significant).

It is important to note that these variables explain only a small percentage of the variation in returns. In a multivariate regression that includes these eleven variables, the adjusted R-squared is 0.085.[158] In other words, returns to the non-agricultural sector are driven primarily by unobservables, which could explain why it is difficult for households to calculate their returns to the non-agricultural sector and therefore why suboptimal sorting decisions are common, as we discuss in the following sub-section.

aversion (maximum) yield statistically significant coefficients.

[158]The adjusted R-squared is roughly the same (and in fact, slightly smaller) for a multivariate regressions with all 27 variables originally included in the LASSO.

17.4 Misallocation

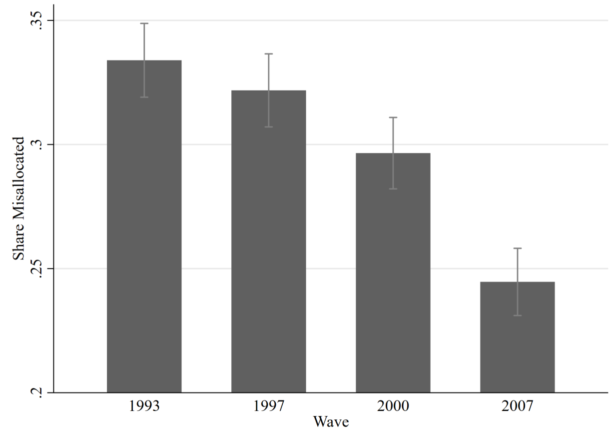
Because households switch in and out of the non-agricultural sector as they learn more information about their η_i, many households spend time in a sector which is suboptimal. To identify households that are misallocated, we use the household's beliefs about its relative productivity going into the final period (m_{i4}), and calculate its expected return to the non-agricultural sector using this value ($\beta + m_{i4}$). Households with a positive return should be in the non-agricultural sector, while households with a negative return should be in agriculture.[159] Based on this information, we characterize households as misallocated if they are not in their optimal sector. Figure 22 shows that a large share of households are misallocated in each wave. This share declines from 33% in 1993 to 24% in 2007, indicating that households are learning about their true η_i and becoming increasingly likely to select their optimal sector.[160]

We next explore the costs of this misallocation, represented by the absolute value of non-agricultural returns (calculated using final beliefs about η_i, as described above) among misallocated households. Misallocated households who are currently in agriculture but should be in the non-agricultural sector have a positive return, which represents unrealized income gains due to their misallocation. Similarly, misallocated households who are currently in the non-agricultural sector but should be in agriculture have a negative return, the absolute value of which represents how much more they could have earned if they had chosen the agricultural sector instead. We sum all of these misallocation amounts for each wave and divide by the total number of households

[159] Note that the underlying incomes and, as a result, these estimated returns are in terms of *net* earnings. As such, any costs of engaging in either activity are already accounted for.

[160] Remember that the sample is a balanced panel such that these patterns are not driven by the entry of new households.

Figure 22: Share of Households Misallocated

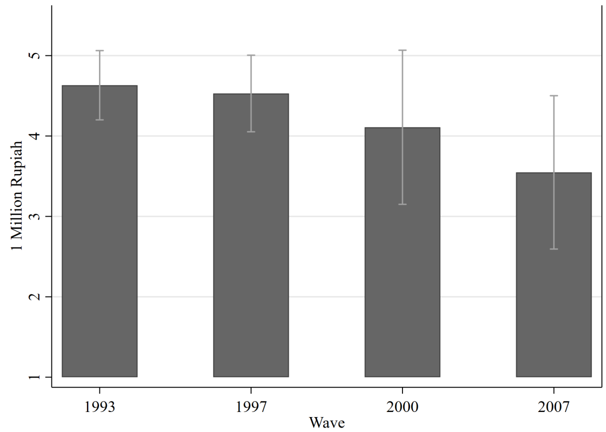


Notes: Misallocated households are defined as those with final returns ($\beta + m_{i4}$) greater than zero but in the agricultural sector, or those with final returns less than zero but in the non-agricultural sector. Error bars denote 95% confidence intervals.

in the sample. We plot these values in Figure 23. Misallocation leads to losses of around 4.5 million rupiah (about 325 USD) per household in 1993. This declines over time, driven both by reductions in the share of misallocated households and the extent of their misallocation. That is, as households converge over time and beliefs become more precise, fewer households are misallocated and the remaining misallocated households are more "marginally" misallocated with smaller average forgone earnings per misallocated household.

We can also express these amounts as a fraction of total potential income (which is equal to a misallocated household's realized income plus their return). As we show in Appendix Figure X.3, misallocated amounts correspond to 64% of misallocated households' potential income overall in 1993. Put differently, misallocated households earn 64% less than they could have had they been in their optimal sector. This figure decreases to around 50% in 2007.

Figure 23: Average Misallocated Income



Notes: A household's misallocated income is equal to zero if they are not misallocated, and equal to the absolute value of their estimated final return ($\beta + m_{i4}$) if they are misallocated. Standard errors are calculated analytically (see Appendix Y.2).

17.5 Alternative Models

As described above, our empirical strategy can recover consistent estimates of β and ϕ (as long as sequential exogeneity still holds), even if the learning structure outlined above is not the main driver of the switching dynamics we observe in the data. In this section, we discuss some of these alternative models and evaluate whether our evidence is consistent with them.

17.5.1 Land Market Frictions

Frictions in land markets have been proposed as an important potential source of misallocation (Chen, 2017, Adamopoulos et al., 2017, Adamopoulos and Restuccia, 2020), but we argue that they are unlikely to be the primary driver of the sorting patterns we document here for several reasons. First, the substantial, bilateral, high frequency churning in Figure 16 is inconsistent with the idea that land market frictions are driving the dynamic sorting patterns we attempt to explain in this essay, as such frictions should restrict switching out of and into agriculture substantially.

In addition, households in our sample do not appear to be substantially constrained in their ability to buy and sell land. For example, using IFLS survey questions on land ownership at the household level, we find that around half of households in our sample change land ownership status at least once in the study period (i.e., they go from owning no land to owning land or vice versa).[161] In spite of this, we acknowledge that some sort of land friction could still be a source of misallocation in our context. We explicitly aim to cut past these issues by absorbing community by year fixed effects. The fact that we find misallocation even after controlling for these fixed effects suggests that something other than market level frictions must be driving the misallocation we document.

17.5.2 Saving out of Financial Constraints

Households might save to relax financial constraints or overcome switching costs, and this could be a separate reason why households switch sectors and appear to have evolving (perceptions of) η_i. However, this explanation is at odds with Figure X.1, which shows that switching declines with the amount of time spent in a given sector. If households were saving to overcome switching costs, we would expect to see the opposite pattern. In addition, because we

[161] While one may worry that part of this could be due to measurement error, or the inclusion or departure of land-owning household members, we also find that 12% of households who owned land for a farm business at any point during the study period reported either buying or selling that land during this time. The IFLS does not ask about sales or purchases of land owned for a non-farm business after the 1997 wave, and does not ask about sales or purchases of other land owned (not for the purpose of any business) after the 1993 wave, which means we cannot calculate this statistics for the full sample. But if anything, this statistic we are able to obtain substantially underestimates the land transactions in our sample.

absorb community by year fixed effects, our estimates are not picking up the effects of any formal or informal borrowing conditions that vary at the community by wave level (for example, the existence, strength, and/or aggregate resources of informal borrowing networks in a village).

17.5.3 Learning by Doing

If households accumulate the skills that are more valuable in a sector while participating in that sector, this would generate evolutions in η_i over time. That is, with $\phi < 0$, η_i would go up with time spent in the agricultural sector and go down with time spent in the non-agricultural sector.[162] As long as the evolution process is a martingale such that sequential exogeneity is still valid, this would not prevent our strategy from obtaining consistent estimates of β and ϕ. However, this learning by doing process would result in a different pattern for the evolution of η_i (and therefore expected returns), and importantly would not imply any misallocation of labor.

To determine whether this learning mechanism appears consistent with the data, we examine how expected returns evolve for households from the end of period $t-1$ to the end of period t, separately for agricultural and non-agricultural households. Under a learning by doing model, we would expect returns to the non-agricultural sector to decrease from $t-1$ to t, for those who are in agriculture in period t (because they improve their skills in agriculture

[162]An alternative learning structure that could be relevant to our context is the multi-armed bandit problem. That is, households might choose in advance the optimal sector or even sequence of sectoral choices in order to learn about or invest in building their η_i. Under this scenario, households would choose to invest in the sector they believe is most likely to be best for them for several periods and hope to accumulate skill there. Only those who learn they have very low sector-specific skill in their chosen sector or who suffer a very large relative earnings shock would eventually switch, and would be very unlikely to ever switch back. This scenario is completely at odds with the high-frequency bilateral switching in Figure 16.

during that period). At the same time, we would expect returns to the non-agricultural sector to increase from $t-1$ to t for those in the non-agricultural sector, as they improve their non-agricultural skills while in that sector.

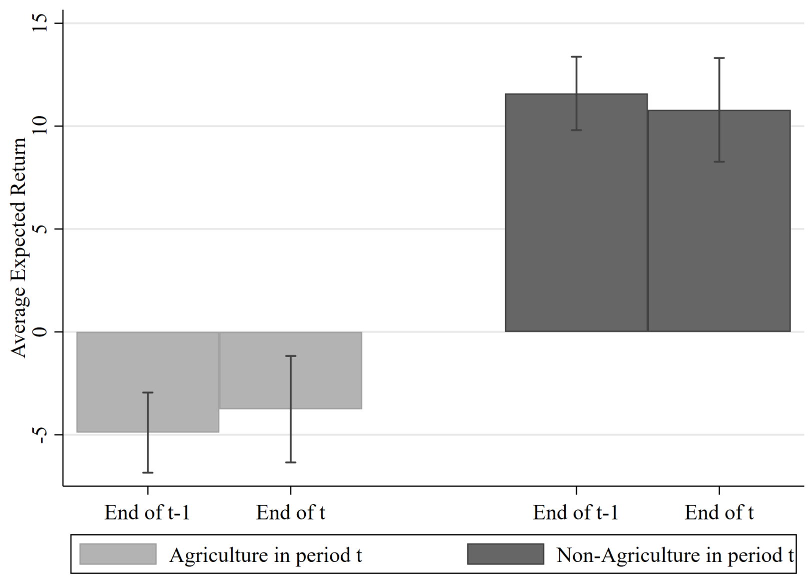
This is not what we find in Figure 24. The first pair of light gray bars shows that expected returns are statistically unchanged from the end of period $t-1$ to the end of period t for those in the agricultural sector in period t. The second pair of dark gray bars shows that expected returns are also unchanged for those in the non-agricultural sector from period period $t-1$ to t.

This flat pattern for each sector is precisely what our proposed learning process would predict. That is, the updates to η_i, unconditional on future decisions, are assumed to have a martingale structure such that further innovations should be mean 0 after switching. As such, this pattern is both inconsistent with a learning by doing interpretation and a strong confirmation of precisely the learning about comparative advantage model we propose.

18 Conclusion

We hypothesize that imperfect information about relative productivity across sectors might lead households to select suboptimally early in their productive life cycles. We use a dynamic sectoral sorting framework to study the household's decision to participate in the non-agricultural sector. Previous studies have modeled selection as a one-off sorting decision across sectors, limiting the ability to document sectoral sorting mistakes along households' productive life cycles. We document substantial churning along the sectoral margin, an empirical regularity across most developing countries, and show that this churning reduces with experience in a sector.

Figure 24: Evolution of Expected Returns by Sector



Notes: The figure reports the average return to the non-agricultural sector ($\beta + \phi m_{it}$) in $t-1$ and t, separately for households in the agricultural and non-agricultural sector. Because returns can only be estimated for the first four periods and because we also calculate a one period lag, we restrict to the three middle waves (1997, 2000, and 2007). Error bars denote 95% confidence intervals. Standard errors are calculated analytically (see Appendix Y.2).

Using an extension of projection-based panel methods to estimate a generalized earnings equation with dynamic correlated random coefficients, we find many households spend substantial amounts of time in a sector which is suboptimal for them, earning 64% less on average than they could have if they were properly sorted across sectors. That is, structural estimates confirm that the sectoral churning is, at least in part, due to substantial learning about relative abilities across sectors and slow convergence to optimal sectors.

Our approach nests several alternative models which can be ruled out. For example, we can estimate a model with comparative advantage but no dynamics as well as a model with neither dynamics nor heterogeneity in relative earnings across sectors. We find that dynamics are important and in fact that the heterogeneity in relative earnings across sectors is only well fit (and substantial) when allowing for dynamics. Finally, we also evaluate alternative interpretations for the dynamic heterogeneity we observe in the data. We consider whether land market frictions, saving out of financial constraints, or skill accumulation (i.e., learning by doing) could explain the patterns we observe in the raw data as well as the structural parameters we recover, and find each of these alternative interpretations to be less consistent with our findings than learning about comparative advantage.

IV

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V

Appendices for Chapter I: Effect of Minimum Wages on Automation and Offshoring Decisions of Firms

A Original schedule of the minimum wages act, 1948

Part I-Non-agricultural occupations

1. Employment in any woolen carpet making or shawl weaving establishment.
2. Employment in any rice mill flour mill or dal mill.
3. Employment in any tobacco (including bidi making) manufactory.
4. Employment in any plantation that is to say any estate which is maintained for the purpose of growing cinchona rubber tea or coffee.
5. Employment in any oil mill.
6. Employment under any local authority.
7. Employment on the construction or maintenance of roads or in building operations.
8. Employment in stone breaking or stone crushing.

9. Employment in any lac manufactory.
10. Employment in any mica works.
11. Employment in public mo tor transport.
12. Employment in tanneries and leather manufactory.
13. Employment in gypsum mines.
14. Employment in barytes mines.
15. Employment in bauxite mines.
16. Employment in manganese mines.
17. Employment in the maintenance of buildings and employment in the construction and maintenance of runways.
18. Employment in china clay mines.
19. Employment in kyantite mines.
20. Employment in copper mines.
21. Employment in clay mines covered under the Mines Act 1952 (35 of 195 2).
22. Employment in magnesite mines covered under the Mines Act 1952 (35 of 195 2).
23. Employment in white clay mines.
24. Employment in stone mines.

Part II-Non-agricultural occupations

(1) Employment in agriculture that is to say in any form of farming including the cultivation and tillage of the soil, dairy farming, the production, cultivation, growing and harvesting of any agricultural or horticultural commodity, the raising of live-stock, bees or poultry and any practice performed by a farmer or on a farm as incidental to or in conjunction with farm operation (including any forestry or timbering operations and the preparation for market and delivery to storage or to market or to carriage for transportation to market farm produce).

B Definition of key variables

The Prowess data dictionary defines the plant and machinery as follow:

> Plant and machinery are essentially production facilities, typically for manufacturing goods. Examples for plant & machinery are air conditioner plant, furnace, boiler, water pumps, effluent treatment plant (ETP), water treatment plant, moulds, tools, weighing scale, hydraulic works, construction equipment, medical equipment and surgical instrument, studio equipment, testing equipment, windmill, workshop equipment, factory equipment, etc.

Importantly, electrical installations are defined as follows:

> Electrical installations includes electrical machinery, energy saving devices, UPS, generator/ diesel generator set, transformers, etc. Electrical machinery includes switchgear, transformers and other stationary plant and wiring, fitting of electric light and fan installations.
>
> Electrical installations are often reported along with plant and machinery by companies in their Annual Report. If the electrical installation assets can be segregated then it is reported separately in Prowess. Else, it is reported along with plant and machinery in Prowess.

Since, most firms do not distinguish between electrical machinery and non-electrical machinery, I sum the two categories above for the firms that do segregate between the two. Note that buildings are not included, hence the resulting plant and machinery category includes only physical equipment required for the production.

The computer category includes computers and peripheral IT systems. Since software and computers are intrinsically linked, I add software to this category. Just like before, this choice is also driven by the fact that it's not clear if all firms report software separately from the computer category.

The profit margin variable used in the essay is defined as follows:

> The percentage of profit that a company generated from the total income it earned during a period, after meeting all the expenses but before paying direct taxes.

The documentation states that this variable provides a comparable profit metric to compare firms within and across industries.

From the ASI documentation, total employee compensations

> are defined to include all remuneration in monetary terms and also payable more or less regularly in each pay period to workers as compensation for work done during the accounting year. It includes (a) direct wages and salary (i.e., basic wages/salaries, payment of overtime, dearness, compensatory, house rent and other allowances) (b) remuneration for the period not worked (i.e., basic wages, salaries and allowances payable for leave period, paid holiday, lay- off payments and compensation for unemployment, if not paid from sources other than employers) (c) bonus and ex-gratia payment paid both at regular and less frequent intervals (i.e., incentive bonuses, productive bonuses, profit sharing bonuses, festival

or year-end bonuses etc.) It excludes lay off payments which are made from trust or other special funds set up exclusively for this purpose i.e., payments not made by the employer. It also excludes imputed value of benefits in kind, employer's contribution to old age benefits and other social security charges, direct expenditure on maternity benefits creches and other group benefits Traveling and other expenditure incurred for business purposes and reimbursed by the employer are excluded. The wages are expressed in terms of gross value i.e., before deduction for fines, damages, taxes, provident fund, employee's state insurance contribution etc.

C Binding minimum wage

Table C.1: Effect of a minimum wage increase on wages using household survey data

	(1) Daily wage	(2) Daily wage
Minimum wage	0.281**	0.312**
	(0.118)	(0.131)
Minimum wage X RTI		-0.185
		(0.132)
Minimum wage X Offshore		0.272***
		(0.0868)
Observations	10527	10527
Mean of Y	134.7	134.7
SD	169.4	169.4

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. India's National Sample Survey collects data on employment for individuals in the 14-65 age range every five years or so. The 2000, 2005, and 2008 waves contain employment data. I compile the wage of all individuals in these waves. I regress the wage of employed individuals on the real minimum wages in Column (1). In Column (2), I also include the interactions between the minimum wages and the routineness and offshorability indexes. All specifications include district, year, four-digit-industry fixed effects, and three-digit-occupation fixed effects. All specifications use the sample weights provided in the surveys. I report White standard errors in parenthesis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. I exclude observations in states and industries where no statutory minimum wages exist. The minimum wage data spans from 2002-2008. When merging in the wage data to the survey data, I attribute the 2002 wages to the 2000 employment wave. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

D Marginal effects for employment regressions

Table D.1: Effect of a minimum wage increase on the number of employees working in a typical workday

	(1) Pooled	(2) Group 1	(3) Group 2	(4) Group 3	(5) Group 4
Minimum wage	-0.0137	-0.328***	-0.0619*	-0.0534	0.114***
	(0.0208)	(0.100)	(0.0354)	(0.0363)	(0.0325)
MinXContract	0.0368	0.536***	0.0975*	0.0988	-0.118**
	(0.0356)	(0.159)	(0.0568)	(0.0620)	(0.0492)
MinXManager	-0.00273	0.492***	0.0657	0.0228	-0.172***
	(0.0279)	(0.143)	(0.0455)	(0.0478)	(0.0466)
MinXRTI	0.193***	0.152**	0.178***	0.307**	0.0852
	(0.0508)	(0.0615)	(0.0609)	(0.119)	(0.0593)
MinXRTIXContract	-0.325***	-0.236**	-0.251***	-0.488***	-0.210**
	(0.0830)	(0.0978)	(0.0968)	(0.188)	(0.0936)
MinXRTIXManager	-0.278***	-0.213***	-0.231***	-0.432***	-0.163*
	(0.0701)	(0.0695)	(0.0727)	(0.158)	(0.0853)
MinXOff	-0.166***	-0.153***	-0.241***	-0.131**	-0.205***
	(0.0472)	(0.0568)	(0.0836)	(0.0597)	(0.0711)
MinXOffXContract	0.302***	0.218***	0.345**	0.193**	0.362***
	(0.0762)	(0.0766)	(0.136)	(0.0974)	(0.117)
MinXOffXManager	0.279***	0.201***	0.322***	0.165*	0.349***
	(0.0675)	(0.0702)	(0.116)	(0.0868)	(0.0991)
Observations	420051	42270	45483	84618	244998
Mean of Y	39.59	36.44	30.74	44.88	40.17
SD	76.50	76.34	67.74	85.37	74.97

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress the number of employees working during a typical 8-hour workday on the real minimum wages and the interaction between these wages and the routineness and offshorability indexes. Each variable is further interacted with the type of employee, namely, contract workers and managers. Regular workers are the excluded type of employee. Column (1) reports the results for all firms. Columns (2)-(5) report the results for firms in the first-fourth compensation groups, respectively. For every district, industry, year, I compute the median compensation per day across firms for regular workers and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample. Columns (2)-(5) reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%, between 105 and 130%, between 130 and 180%, and above 180% of the average minimum wage in the district over the study period, respectively. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% of values of the dependent variable are winsorized. All firms with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table D.2: Effect of a minimum wage increase on the number of mandays

	(1) Pooled	(2) Group 1	(3) Group 2	(4) Group 3	(5) Group 4
Minimum wage	-3.642	-84.07***	-13.28	-16.04	31.73***
	(5.593)	(23.50)	(10.46)	(10.75)	(8.024)
MinXContract	8.427	133.9***	21.75	26.29	-31.52***
	(9.215)	(37.49)	(16.11)	(17.46)	(11.96)
MinXManager	0.152	122.5***	16.43	6.558	-47.62***
	(7.655)	(33.72)	(13.65)	(14.58)	(11.49)
MinXRTI	56.45***	36.62**	57.80***	91.42**	24.91
	(14.99)	(16.51)	(19.53)	(35.51)	(17.33)
MinXRTIXContract	-92.70***	-64.06**	-77.31***	-144.1***	-61.35**
	(24.02)	(26.16)	(29.92)	(55.70)	(27.11)
MinXRTIXManager	-82.46***	-59.14***	-74.28***	-130.0***	-48.62*
	(20.83)	(17.22)	(24.64)	(47.86)	(25.10)
MinXOff	-55.49***	-51.48***	-86.04***	-39.55**	-67.70***
	(15.55)	(18.00)	(28.51)	(18.90)	(21.96)
MinXOffXContract	98.68***	72.52***	114.9**	62.33**	118.7***
	(24.94)	(23.59)	(46.02)	(30.43)	(35.69)
MinXOffXManager	92.85***	67.02***	108.7***	55.03**	115.6***
	(22.14)	(21.66)	(40.26)	(27.31)	(30.09)
Observations	420051	42270	45483	84618	244998
Mean of Y	11690.0	9926.0	8950.9	13563.5	11929.5
SD	23067.7	21719.8	20604.9	26111.5	22634.2

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress the number of 8-hour workdays paid to each group of employee over the year on the real minimum wages and the interaction between these wages and the routineness and offshorability indexes. Each variable is further interacted with the type of employee, namely, contract workers and managers. Regular workers are the excluded type of employee. Column (1) reports the results for all firms. Columns (2)-(5) report the results for firms in the first-fourth compensation groups, respectively. For every district, industry, year, I compute the median compensation per day across firms for regular workers and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample. Columns (2)-(5) reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%, between 105 and 130%, between 130 and 180%, and above 180% of the average minimum wage in the district over the study period, respectively. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% of values of the dependent variable are winsorized. All firms with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

E Robustness to winsorizing highest 1% of values

Table E.1: Effect of a minimum wage increase on overall capital investment-winsorizing top and bottom 1% of values

	Capital			
	(1)	(2)	(3)	(4)
Minimum wage	-0.00951	-0.151	0.0160	-0.145
	(0.106)	(0.154)	(0.115)	(0.153)
Minimum wage X RTI		0.626*		0.816**
		(0.359)		(0.391)
Minimum wage X Offshore			-0.228	-0.441*
			(0.227)	(0.239)
Observations	54997	54997	54997	54997
Mean of Y	23.57	23.57	23.57	23.57
SD	160.0	160.0	160.0	160.0

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress investment on real minimum wages in Column (1). I also include the interaction between the real minimum wages and the routineness index in Column (2). In Column (3), I include the interaction between the real minimum wages and the index of offshorability. Column (4) is the preferred specification and includes both interactions. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. All specifications include fourth-degree polynomials in age, lagged revenue, lagged profit margin, and revenue growth. Standard errors are clustered at the four-digit-industry-by-state level. The largest 1% and smallest 1% of values of the dependent variable are winsorized. All firms with positive net value in machinery and/or computers for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table E.2: Effect of a minimum wage increase on investment in machinery-winsorizing top and bottom 1% of values

	Machinery			
	(1)	(2)	(3)	(4)
Minimum wage	-0.0145	-0.0815	0.00900	-0.0768
	(0.0783)	(0.105)	(0.0825)	(0.104)
Minimum wage X RTI		0.296		0.436
		(0.247)		(0.270)
Minimum wage X Offshore			-0.211	-0.324*
			(0.156)	(0.168)
Observations	54997	54997	54997	54997
Mean of Y	13.52	13.52	13.52	13.52
SD	96.08	96.08	96.08	96.08

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress machinery investment on real minimum wages in Column (1). I also include the interaction between the real minimum wages and the routineness index in Column (2). In Column (3), I include the interaction between the real minimum wages and the index of offshorability. Column (4) is the preferred specification and includes both interactions. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. All specifications include fourth-degree polynomials in age, lagged revenue, lagged profit margin, and revenue growth. Standard errors are clustered at the four-digit-industry-by-state level. The largest 1% and smallest 1% of values of the dependent variable are winsorized. All firms with positive net value in machinery and/or computers for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table E.3: Effect of a minimum wage increase on investment in computers-winsorizing top and bottom 1% of values

	Computers			
	(1)	(2)	(3)	(4)
Minimum wage	-0.0462	-0.0704	-0.0311	-0.0678
	(0.0513)	(0.0664)	(0.0546)	(0.0645)
Minimum wage X RTI		0.107		0.186
		(0.180)		(0.193)
Minimum wage X Offshore			-0.135	-0.184
			(0.128)	(0.137)
Observations	54997	54997	54997	54997
Mean of Y	11.97	11.97	11.97	11.97
SD	100.0	100.0	100.0	100.0

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress computer investment on real minimum wages in Column (1). I also include the interaction between the real minimum wages and the routineness index in Column (2). In Column (3), I include the interaction between the real minimum wages and the index of offshorability. Column (4) is the preferred specification and includes both interactions. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. All specifications include fourth-degree polynomials in age, lagged revenue, lagged profit margin, and revenue growth. Standard errors are clustered at the four-digit-industry-by-state level. The largest 1% and smallest 1% of values of the dependent variable are winsorized. All firms with positive net value in machinery and/or computers for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table E.4: Effect of a minimum wage increase on the number of employees working in a typical workday- winsorizing top 1% of values

	(1) Pooled	(2) Group 1	(3) Group 2	(4) Group 3	(5) Group 4
Minimum wage	-0.00193	-0.421***	-0.0989**	-0.0656	0.161***
	(0.0255)	(0.141)	(0.0491)	(0.0489)	(0.0463)
MinXContract	0.0171	0.612***	0.109	0.134*	-0.175**
	(0.0418)	(0.215)	(0.0753)	(0.0797)	(0.0698)
MinXManager	-0.0230	0.578***	0.0849	0.0291	-0.245***
	(0.0346)	(0.202)	(0.0644)	(0.0682)	(0.0663)
MinXRTI	0.287***	0.218**	0.210***	0.458**	0.219**
	(0.0756)	(0.0971)	(0.0731)	(0.199)	(0.104)
MinXRTIXContract	-0.459***	-0.281**	-0.308***	-0.700**	-0.379**
	(0.121)	(0.143)	(0.114)	(0.299)	(0.164)
MinXRTIXManager	-0.428***	-0.301***	-0.304***	-0.653**	-0.333**
	(0.107)	(0.106)	(0.0883)	(0.263)	(0.155)
MinXOff	-0.261***	-0.186**	-0.279***	-0.183**	-0.411**
	(0.0750)	(0.0791)	(0.106)	(0.0827)	(0.175)
MinXOffXContract	0.467***	0.272**	0.443***	0.261*	0.695**
	(0.116)	(0.113)	(0.165)	(0.145)	(0.279)
MinXOffXManager	0.439***	0.267**	0.425***	0.223*	0.666***
	(0.106)	(0.107)	(0.140)	(0.131)	(0.254)
Observations	420051	42270	45483	84618	244998
Mean of Y	52.04	45.91	38.80	60.15	53.05
SD	128.1	123.6	108.2	146.5	125.8

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress the number of employees working during a typical 8-hour workday on the real minimum wages and the interaction between these wages and the routineness and offshorability indexes. Each variable is further interacted with the type of employee, namely, contract workers and managers. Regular workers are the excluded type of employee. Column (1) reports the results for all firms. Columns (2)-(5) report the results for firms in the first-fourth compensation groups, respectively. For every district, industry, year, I compute the median compensation per day across firms for regular workers and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample. Columns (2)-(5) reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%, between 105 and 130%, between 130 and 180%, and above 180% of the average minimum wage in the district over the study period, respectively. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 1% of values of the dependent variable are winsorized. All firms with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table E.5: Total effect of a minimum wage increase on the number of employees working in a typical workday- winsorizing top 1% of values

	(1) Pooled	(2) Group 1	(3) Group 2	(4) Group 3	(5) Group 4
Minimum wage	0	-1.05***	-.25**	-.16	.4***
	(.064)	(.352)	(.123)	(.122)	(.116)
MinXContract	.04	.48**	.03	.17*	-.04
	(.047)	(.211)	(.082)	(.091)	(.07)
MinXManager	-.06*	.39**	-.04	-.09	-.21***
	(.032)	(.181)	(.065)	(.069)	(.062)
MinXRTI	.71***	-.51	.28	.98**	.95***
	(.202)	(.32)	(.21)	(.468)	(.311)
MinXRTIXContract	-.39***	.32	-.22	-.44*	-.44**
	(.123)	(.241)	(.168)	(.23)	(.2)
MinXRTIXManager	-.41***	.19	-.27**	-.58***	-.49***
	(.101)	(.182)	(.127)	(.173)	(.169)
MinXOff	-.66***	-1.52***	-.95***	-.62***	-.63
	(.18)	(.351)	(.273)	(.22)	(.393)
MinXOffXContract	.55***	.69***	.43***	.36*	.67***
	(.111)	(.248)	(.178)	(.193)	(.242)
MinXOffXManager	.38***	.6***	.33***	.01	.43**
	(.088)	(.223)	(.125)	(.165)	(.191)
Observations	420051	42270	45483	84618	244998
Mean of Y	52.04	45.91	38.80	60.15	53.05
SD	128.1	123.6	108.2	146.5	125.8

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress the number of employees working during a typical 8-hour workday on the real minimum wages and the interaction between these wages and the routineness and offshorability indexes. Each variable is further interacted with the type of employee, namely, contract workers and managers. Regular workers are the excluded type of employee. I compute the total effect of a typical real minimum wage increase of 2.5 rupee for each type of employee. Column (1) reports the results for all firms. Columns (2)-(5) report the results for firms in the first-fourth compensation groups, respectively. For every district, industry, year, I compute the median compensation per day across firms for regular workers and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample. Columns (2)-(5) reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%, between 105 and 130%, between 130 and 180%, and above 180% of the average minimum wage in the district over the study period, respectively. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 1% of values of the dependent variable are winsorized. All firms with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table E.6: Effect of a minimum wage increase on the number of mandays-winsorizing top 1% of values

	(1) Pooled	(2) Group 1	(3) Group 2	(4) Group 3	(5) Group 4
Minimum wage	0.593	-105.4***	-26.57*	-20.86	48.15***
	(7.206)	(29.21)	(15.00)	(14.82)	(12.32)
MinXContract	1.885	146.9***	24.81	36.36	-48.60***
	(11.31)	(44.61)	(22.09)	(23.47)	(18.44)
MinXManager	-6.708	138.9***	22.31	7.547	-70.32***
	(9.826)	(41.63)	(19.64)	(20.97)	(17.54)
MinXRTI	85.97***	58.52**	65.52***	139.6**	65.66**
	(22.40)	(26.85)	(24.64)	(59.88)	(30.67)
MinXRTIXContract	-136.0***	-77.86**	-100.5***	-211.0**	-116.6**
	(35.41)	(38.54)	(37.06)	(89.64)	(47.91)
MinXRTIXManager	-130.3***	-86.05***	-102.5***	-199.5**	-103.7**
	(31.69)	(26.48)	(31.00)	(79.54)	(45.60)
MinXOff	-91.39***	-67.17***	-101.6***	-62.15**	-139.1***
	(24.45)	(25.34)	(38.59)	(26.72)	(51.94)
MinXOffXContract	158.5***	95.93***	154.3***	91.92**	231.6***
	(37.19)	(36.08)	(58.45)	(45.73)	(82.28)
MinXOffXManager	151.4***	94.27***	151.2***	81.35*	223.9***
	(33.71)	(33.98)	(50.85)	(41.48)	(74.39)
Observations	420051	42270	45483	84618	244998
Mean of Y	15739.0	12507.3	11638.3	18578.4	16174.7
SD	39984.8	35213.2	34329.1	46094.1	39532.9

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress the number of 8-hour workdays paid to each group of employee over the year on the real minimum wages and the interaction between these wages and the routineness and offshorability indexes. Each variable is further interacted with the type of employee, namely, contract workers and managers. Regular workers are the excluded type of employee. Column (1) reports the results for all firms. Columns (2)-(5) report the results for firms in the first-fourth compensation groups, respectively. For every district, industry, year, I compute the median compensation per day across firms for regular workers and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample. Columns (2)-(5) reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%, between 105 and 130%, between 130 and 180%, and above 180% of the average minimum wage in the district over the study period, respectively. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 1% of values of the dependent variable are winsorized. All firms with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table E.7: Total effect of a minimum wage increase on the number of mandays-winsorizing top 1% of values

	(1) Pooled	(2) Group 1	(3) Group 2	(4) Group 3	(5) Group 4
Minimum wage	1.48	-263.52***	-66.42*	-52.15	120.38***
	(18.014)	(73.036)	(37.499)	(37.043)	(30.797)
MinXContract	6.19	103.71**	-4.39	38.74	-1.11
	(12.31)	(50.543)	(23.234)	(26.089)	(20.029)
MinXManager	-15.29	83.68*	-10.63	-33.28	-55.41***
	(9.341)	(44.419)	(20.325)	(21.301)	(17.661)
MinXRTI	216.41***	-117.21	97.38	296.8**	284.52***
	(60.581)	(81.298)	(69.922)	(140.83)	(91.326)
MinXRTIXContract	-118.99***	55.37	-91.81	-139.91**	-128.55**
	(36.465)	(69.794)	(56.051)	(69.546)	(59.345)
MinXRTIXManager	-126.07***	14.87	-103.03**	-183.08***	-150.54***
	(29.837)	(50.851)	(46.012)	(53.417)	(49.235)
MinXOff	-227***	-431.44***	-320.48***	-207.51***	-227.37**
	(57.243)	(89.633)	(98.41)	(70.611)	(115.319)
MinXOffXContract	174.06***	175.61***	127.4**	113.19*	230.15***
	(33.257)	(69.437)	(61.671)	(58.686)	(70.5)
MinXOffXManager	134.85***	151.42***	113.42***	14.72	156.66***
	(26.076)	(61.419)	(47.934)	(51.015)	(54.147)
Observations	420051	42270	45483	84618	244998
Mean of Y	15739.0	12507.3	11638.3	18578.4	16174.7
SD	39984.8	35213.2	34329.1	46094.1	39532.9

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress the number of 8-hour workdays paid to each group of employee over the year on the real minimum wages and the interaction between these wages and the routineness and offshorability indexes. Each variable is further interacted with the type of employee, namely, contract workers and managers. Regular workers are the excluded type of employee. I compute the total effect of a typical real minimum wage increase of 2.5 rupee for each type of employee. Column (1) reports the results for all firms. Columns (2)-(5) report the results for firms in the first-fourth compensation groups, respectively. For every district, industry, year, I compute the median compensation per day across firms for regular workers and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample. Columns (2)-(5) reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%, between 105 and 130%, between 130 and 180%, and above 180% of the average minimum wage in the district over the study period, respectively. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 1% of values of the dependent variable are winsorized. All firms with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

F Robustness using variation from firms in districts along state borders

Table F.1: Effect of a minimum wage increase on overall capital investment-contiguous district design

	Capital			
	(1)	(2)	(3)	(4)
Minimum wage	-0.00954	-0.0581	-0.00450	-0.0585
	(0.0539)	(0.0650)	(0.0563)	(0.0643)
Minimum wage X RTI		0.219		0.276*
		(0.148)		(0.164)
Minimum wage X Offshore			-0.0583	-0.141
			(0.114)	(0.126)
Observations	191715	191715	191715	191715
Mean of Y	12.01	12.01	12.01	12.01
SD	67.87	67.87	67.87	67.87

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress investment on real minimum wages in Column (1). I also include the interaction between the real minimum wages and the routineness index in Column (2). In Column (3), I include the interaction between the real minimum wages and the index of offshorability. Column (4) is the preferred specification and includes both interactions. In this exercise, districts along state lines are paired to contiguous districts in other states. If a district shares a border with $n \geq 1$ disttricts in other states, the observations of that district are repeated n times. Fixed effects are included for every district pair. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. All specifications include fourth-degree polynomials in age, lagged revenue, lagged profit margin, and revenue growth. Standard errors are clustered at the four-digit-industry-by-state level. The largest 2.5% and smallest 1% of values of the dependent variable are winsorized. All firms in contiguous districts with positive net value in machinery and/or computers for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table F.2: Effect of a minimum wage increase on investment in machinery-contiguous district design

	Machinery			
	(1)	(2)	(3)	(4)
Minimum wage	-0.0172	-0.0409	-0.0130	-0.0411
	(0.0439)	(0.0545)	(0.0456)	(0.0539)
Minimum wage X RTI		0.107		0.143
		(0.127)		(0.141)
Minimum wage X Offshore			-0.0485	-0.0916
			(0.0944)	(0.106)
Observations	191715	191715	191715	191715
Mean of Y	7.552	7.552	7.552	7.552
SD	48.94	48.94	48.94	48.94

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress machinery investment on real minimum wages in Column (1). I also include the interaction between the real minimum wages and the routineness index in Column (2). In Column (3), I include the interaction between the real minimum wages and the index of offshorability. Column (4) is the preferred specification and includes both interactions. In this exercise, districts along state lines are paired to contiguous districts in other states. If a district shares a border with $n \geq 1$ disttricts in other states, the observations of that district are repeated n times. Fixed effects are included for every district pair. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. All specifications include fourth-degree polynomials in age, lagged revenue, lagged profit margin, and revenue growth. Standard errors are clustered at the four-digit-industry-by-state level. The largest 2.5% and smallest 1% of values of the dependent variable are winsorized. All firms in contiguous districts with positive net value in machinery and/or computers for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table F.3: Effect of a minimum wage increase on investment in computers-contiguous district design

	Computers			
	(1)	(2)	(3)	(4)
Minimum wage	-0.0325	-0.0407	-0.0180	-0.0412
	(0.0382)	(0.0495)	(0.0380)	(0.0474)
Minimum wage X RTI		0.0370		0.118
		(0.155)		(0.165)
Minimum wage X Offshore			-0.167*	-0.202**
			(0.0927)	(0.0989)
Observations	191715	191715	191715	191715
Mean of Y	8.193	8.193	8.193	8.193
SD	65.72	65.72	65.72	65.72

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress computer investment on real minimum wages in Column (1). I also include the interaction between the real minimum wages and the routineness index in Column (2). In Column (3), I include the interaction between the real minimum wages and the index of offshorability. Column (4) is the preferred specification and includes both interactions. In this exercise, districts along state lines are paired to contiguous districts in other states. If a district shares a border with $n \geq 1$ disttricts in other states, the observations of that district are repeated n times. Fixed effects are included for every district pair. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. All specifications include fourth-degree polynomials in age, lagged revenue, lagged profit margin, and revenue growth. Standard errors are clustered at the four-digit-industry-by-state level. The largest 2.5% and smallest 1% of values of the dependent variable are winsorized. All firms in contiguous districts with positive net value in machinery and/or computers for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table F.4: Effect of a minimum wage increase on the number of employees working in a typical workday- contiguous district design

	(1) Pooled	(2) Group 1	(3) Group 2	(4) Group 3	(5) Group 4
Minimum wage	-0.0251	-0.287***	-0.0321	-0.0694***	0.0979***
	(0.0182)	(0.0771)	(0.0323)	(0.0259)	(0.0316)
MinXContract	0.0455	0.425***	0.0918*	0.0836**	-0.0939**
	(0.0307)	(0.125)	(0.0515)	(0.0410)	(0.0453)
MinXManager	0.0186	0.386***	0.0561	0.0475	-0.146***
	(0.0245)	(0.111)	(0.0372)	(0.0336)	(0.0463)
MinXRTI	0.107***	0.0440	0.177***	0.155***	0.0432
	(0.0312)	(0.0433)	(0.0500)	(0.0415)	(0.0542)
MinXRTIXContract	-0.176***	-0.106*	-0.212***	-0.235***	-0.105
	(0.0514)	(0.0601)	(0.0815)	(0.0702)	(0.0815)
MinXRTIXManager	-0.153***	-0.103**	-0.194***	-0.211***	-0.0805
	(0.0426)	(0.0432)	(0.0535)	(0.0517)	(0.0796)
MinXOff	-0.0721**	0.0126	-0.210***	-0.0817*	-0.0573
	(0.0356)	(0.0463)	(0.0557)	(0.0452)	(0.0592)
MinXOffXContract	0.169***	0.110**	0.272***	0.134**	0.121
	(0.0548)	(0.0535)	(0.0870)	(0.0628)	(0.0899)
MinXOffXManager	0.145***	0.105**	0.243***	0.0902	0.129
	(0.0541)	(0.0477)	(0.0751)	(0.0587)	(0.0848)
Observations	738633	103494	89505	154611	387960
Mean of Y	31.71	27.13	27.09	33.96	33.19
SD	67.54	62.76	64.41	71.46	67.92

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress the number of employees working during a typical 8-hour workday on the real minimum wages and the interaction between these wages and the routineness and offshorability indexes. Each variable is further interacted with the type of employee, namely, contract workers and managers. Regular workers are the excluded type of employee. Column (1) reports the results for all firms. Columns (2)-(5) report the results for firms in the first-fourth compensation groups, respectively. For every district, industry, year, I compute the median compensation per day across firms for regular workers and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample. Columns (2)-(5) reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%, between 105 and 130%, between 130 and 180%, and above 180% of the average minimum wage in the district over the study period, respectively. In this exercise, districts along state lines are paired to contiguous districts in other states. If a district shares a border with $n \geq 1$ disttricts in other states, the observations of that district are repeated n times. Fixed effects are included for every district pair. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% of values of the dependent variable are winsorized. All firms in contiguous districts with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table F.5: Total effect of a minimum wage increase on the number of employees working in a typical workday- contiguous district design

	(1) Pooled	(2) Group 1	(3) Group 2	(4) Group 3	(5) Group 4
Minimum wage	-.06	-.72***	-.08	-.17***	.24***
	(.046)	(.193)	(.081)	(.065)	(.079)
MinXContract	.05	.34***	.15**	.04	.01
	(.036)	(.125)	(.066)	(.052)	(.047)
MinXManager	-.02	.25***	.06	-.05	-.12***
	(.023)	(.097)	(.046)	(.04)	(.048)
MinXRTI	.21**	-.61***	.36***	.22*	.35***
	(.089)	(.225)	(.135)	(.115)	(.151)
MinXRTIXContract	-.12**	.19	.06	-.16*	-.15
	(.056)	(.148)	(.121)	(.098)	(.096)
MinXRTIXManager	-.13***	.1	.02	-.19**	-.21***
	(.051)	(.112)	(.083)	(.084)	(.09)
MinXOff	-.24***	-.69***	-.61***	-.38***	.1
	(.096)	(.201)	(.16)	(.12)	(.167)
MinXOffXContract	.29***	.65***	.3***	.17*	.17
	(.065)	(.151)	(.126)	(.091)	(.104)
MinXOffXManager	.17***	.54***	.14	-.03	.06
	(.055)	(.131)	(.092)	(.079)	(.096)
Observations	738633	103494	89505	154611	387960
Mean of Y	31.71	27.13	27.09	33.96	33.19
SD	67.54	62.76	64.41	71.46	67.92

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress the number of employees working during a typical 8-hour workday on the real minimum wages and the interaction between these wages and the routineness and offshorability indexes. Each variable is further interacted with the type of employee, namely, contract workers and managers. Regular workers are the excluded type of employee. I compute the total effect of a typical real minimum wage increase of 2.5 rupee for each type of employee. Column (1) reports the results for all firms. Columns (2)-(5) report the results for firms in the first-fourth compensation groups, respectively. For every district, industry, year, I compute the median compensation per day across firms for regular workers and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample. Columns (2)-(5) reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%, between 105 and 130%, between 130 and 180%, and above 180% of the average minimum wage in the district over the study period, respectively. In this exercise, districts along state lines are paired to contiguous districts in other states. If a district shares a border with $n \geq 1$ disttricts in other states, the observations of that district are repeated n times. Fixed effects are included for every district pair. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% of values of the dependent variable are winsorized. All firms in contiguous districts with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table F.6: Effect of a minimum wage increase on the number of mandays-contiguous district design

	(1) Pooled	(2) Group 1	(3) Group 2	(4) Group 3	(5) Group 4
Minimum wage	-6.515	-78.70***	-8.837	-20.93***	27.59***
	(5.017)	(21.11)	(9.286)	(7.715)	(8.577)
MinXContract	10.47	110.1***	19.83	22.66*	-24.17**
	(8.012)	(34.07)	(13.45)	(11.58)	(11.98)
MinXManager	5.976	100.8***	13.67	14.54	-39.81***
	(6.858)	(30.55)	(10.61)	(10.08)	(12.33)
MinXRTI	29.97***	6.086	53.80***	45.39***	11.77
	(9.044)	(13.08)	(15.76)	(11.79)	(15.83)
MinXRTIXContract	-48.66***	-26.50	-65.31***	-66.38***	-32.59
	(14.24)	(16.32)	(23.55)	(18.57)	(23.56)
MinXRTIXManager	-44.50***	-27.47**	-61.15***	-62.05***	-24.77
	(12.59)	(12.02)	(18.25)	(15.69)	(23.27)
MinXOff	-24.62**	0.775	-74.10***	-20.00	-21.95
	(11.33)	(15.03)	(19.23)	(13.25)	(18.84)
MinXOffXContract	54.83***	35.65**	91.32***	40.85**	43.41
	(17.46)	(15.64)	(30.08)	(18.75)	(27.92)
MinXOffXManager	49.14***	33.51**	84.24***	29.03	47.00*
	(17.26)	(14.11)	(26.90)	(17.82)	(26.42)
Observations	738633	103494	89505	154611	387960
Mean of Y	9295.1	7471.0	7737.7	10168.3	9819.0
SD	20269.3	17920.3	19441.3	21774.5	20421.5

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress the number of 8-hour workdays paid to each group of employee over the year on the real minimum wages and the interaction between these wages and the routineness and offshorability indexes. Each variable is further interacted with the type of employee, namely, contract workers and managers. Regular workers are the excluded type of employee. Column (1) reports the results for all firms. Columns (2)-(5) report the results for firms in the first-fourth compensation groups, respectively. For every district, industry, year, I compute the median compensation per day across firms for regular workers and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample. Columns (2)-(5) reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%, between 105 and 130%, between 130 and 180%, and above 180% of the average minimum wage in the district over the study period, respectively. In this exercise, districts along state lines are paired to contiguous districts in other states. If a district shares a border with $n \geq 1$ disttricts in other states, the observations of that district are repeated n times. Fixed effects are included for every district pair. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% of values of the dependent variable are winsorized. All firms in contiguous districts with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table F.7: Effect of a minimum wage increase on the number of mandays-contiguous district design

	(1) Pooled	(2) Group 1	(3) Group 2	(4) Group 3	(5) Group 4
Minimum wage	-16.29	-196.75***	-22.09	-52.32***	68.97***
	(12.543)	(52.78)	(23.214)	(19.289)	(21.442)
MinXContract	9.89	78.56**	27.48*	4.33	8.55
	(8.932)	(34.992)	(16.613)	(14.456)	(13.207)
MinXManager	-1.35	55.29**	12.07	-15.96	-30.54**
	(6.392)	(27.98)	(13.282)	(11.963)	(13.668)
MinXRTI	58.65**	-181.53***	112.4***	61.16*	98.41**
	(26.541)	(64.439)	(41.137)	(33.497)	(44.916)
MinXRTIXContract	-36.83**	27.53	-1.32	-48.15*	-43.5
	(16.386)	(43.079)	(32.448)	(26.421)	(29.257)
MinXRTIXManager	-37.66***	1.83	-6.3	-57.6**	-63.04**
	(15.209)	(33.735)	(24.7)	(25.586)	(27.274)
MinXOff	-77.85***	-194.81***	-207.34***	-102.33***	14.1
	(29.205)	(57.084)	(53.95)	(35.706)	(49.831)
MinXOffXContract	85.39***	169.62***	70.54*	56.44**	62.2**
	(19.307)	(46.405)	(37.658)	(25.835)	(31.365)
MinXOffXManager	59.94***	141.01***	37.44	6.61	32.1
	(17.336)	(41.556)	(29.684)	(23.531)	(29.046)
Observations	738633	103494	89505	154611	387960
Mean of Y	9295.1	7471.0	7737.7	10168.3	9819.0
SD	20269.3	17920.3	19441.3	21774.5	20421.5

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress the number of 8-hour workdays paid to each group of employee over the year on the real minimum wages and the interaction between these wages and the routineness and offshorability indexes. Each variable is further interacted with the type of employee, namely, contract workers and managers. Regular workers are the excluded type of employee. I compute the total effect of a typical real minimum wage increase of 2.5 rupee for each type of employee. Column (1) reports the results for all firms. Columns (2)-(5) report the results for firms in the first-fourth compensation groups, respectively. For every district, industry, year, I compute the median compensation per day across firms for regular workers and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample. Columns (2)-(5) reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%, between 105 and 130%, between 130 and 180%, and above 180% of the average minimum wage in the district over the study period, respectively. In this exercise, districts along state lines are paired to contiguous districts in other states. If a district shares a border with $n \geq 1$ disttricts in other states, the observations of that district are repeated n times. Fixed effects are included for every district pair. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% of values of the dependent variable are winsorized. All firms in contiguous districts with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

G Robustness using variation from real wage changes that exceed the inflation level

Table G.1: Effect of a minimum wage increase on overall capital investment-variation from changes larger than the inflation

	Capital			
	(1)	(2)	(3)	(4)
Minimum wage	-0.00989	-0.0821	-0.00720	-0.0808
	(0.0530)	(0.0548)	(0.0572)	(0.0533)
Minimum wage X RTI		0.328**		0.391**
		(0.144)		(0.153)
Minimum wage X Offshore			-0.0283	-0.159
			(0.141)	(0.133)
Observations	54997	54997	54997	54997
Mean of Y	12.29	12.29	12.29	12.29
SD	68.30	68.30	68.30	68.30

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. In this exercise, the real minimum wage is set to its previous value unless the real minimum wage increase between two years exceeds the national inflation rate between these years. I regress investment on real minimum wages in Column (1). I also include the interaction between the real minimum wages and the routineness index in Column (2). In Column (3), I include the interaction between the real minimum wages and the index of offshorability. Column (4) is the preferred specification and includes both interactions. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. All specifications include fourth-degree polynomials in age, lagged revenue, lagged profit margin, and revenue growth. Standard errors are clustered at the four-digit-industry-by-state level. The largest 2.5% and smallest 1% of values of the dependent variable are winsorized. All firms in manufacturing industries with positive net value in machinery and/or computers for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table G.2: Effect of a minimum wage increase on investment in machinery-variation from changes larger than the inflation

	Machinery			
	(1)	(2)	(3)	(4)
Minimum wage	-0.0177	-0.0680	-0.0165	-0.0672
	(0.0462)	(0.0477)	(0.0493)	(0.0465)
Minimum wage X RTI		0.229*		0.270*
		(0.126)		(0.138)
Minimum wage X Offshore			-0.0132	-0.103
			(0.130)	(0.132)
Observations	54997	54997	54997	54997
Mean of Y	7.761	7.761	7.761	7.761
SD	49.27	49.27	49.27	49.27

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. In this exercise, the real minimum wage is set to its previous value unless the real minimum wage increase between two years exceeds the national inflation rate between these years. I regress machinery investment on real minimum wages in Column (1). I also include the interaction between the real minimum wages and the routineness index in Column (2). In Column (3), I include the interaction between the real minimum wages and the index of offshorability. Column (4) is the preferred specification and includes both interactions. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. All specifications include fourth-degree polynomials in age, lagged revenue, lagged profit margin, and revenue growth. Standard errors are clustered at the four-digit-industry-by-state level. The largest 2.5% and smallest 1% of values of the dependent variable are winsorized. All firms in manufacturing industries with positive net value in machinery and/or computers for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table G.3: Effect of a minimum wage increase on investment in computers-variation from changes larger than the inflation

	Computers			
	(1)	(2)	(3)	(4)
Minimum wage	-0.0157	-0.0396	-0.0127	-0.0390
	(0.0292)	(0.0352)	(0.0316)	(0.0344)
Minimum wage X RTI		0.109		0.140
		(0.144)		(0.154)
Minimum wage X Offshore			-0.0315	-0.0780
			(0.0876)	(0.0876)
Observations	54997	54997	54997	54997
Mean of Y	8.332	8.332	8.332	8.332
SD	66.00	66.00	66.00	66.00

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. In this exercise, the real minimum wage is set to its previous value unless the real minimum wage increase between two years exceeds the national inflation rate between these years. I regress computer investment on real minimum wages in Column (1). I also include the interaction between the real minimum wages and the routineness index in Column (2). In Column (3), I include the interaction between the real minimum wages and the index of offshorability. Column (4) is the preferred specification and includes both interactions. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. All specifications include fourth-degree polynomials in age, lagged revenue, lagged profit margin, and revenue growth. Standard errors are clustered at the four-digit-industry-by-state level. The largest 2.5% and smallest 1% of values of the dependent variable are winsorized. All firms in manufacturing industries with positive net value in machinery and/or computers for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table G.4: Effect of a minimum wage increase on the number of employees working in a typical workday- variation from changes larger than the inflation

	(1) Pooled	(2) Group 1	(3) Group 2	(4) Group 3	(5) Group 4
Minimum wage	-0.00346	-0.241**	-0.0203	-0.0413	0.101***
	(0.0202)	(0.112)	(0.0407)	(0.0369)	(0.0308)
MinXContract	0.0219	0.446**	0.0172	0.0920	-0.106**
	(0.0343)	(0.176)	(0.0632)	(0.0601)	(0.0464)
MinXManager	-0.0171	0.428***	-0.0187	0.0199	-0.163***
	(0.0274)	(0.156)	(0.0533)	(0.0472)	(0.0438)
MinXRTI	0.203***	0.163**	0.161**	0.321***	0.104*
	(0.0482)	(0.0733)	(0.0653)	(0.106)	(0.0573)
MinXRTIXContract	-0.323***	-0.249**	-0.264***	-0.468***	-0.221**
	(0.0794)	(0.108)	(0.0955)	(0.174)	(0.0895)
MinXRTIXManager	-0.275***	-0.226***	-0.241***	-0.412***	-0.170**
	(0.0674)	(0.0821)	(0.0740)	(0.147)	(0.0805)
MinXOff	-0.158***	-0.101*	-0.176**	-0.169**	-0.171**
	(0.0455)	(0.0588)	(0.0856)	(0.0664)	(0.0720)
MinXOffXContract	0.263***	0.200**	0.309**	0.175**	0.294**
	(0.0740)	(0.0795)	(0.134)	(0.0888)	(0.118)
MinXOffXManager	0.245***	0.185**	0.289**	0.151*	0.290***
	(0.0652)	(0.0719)	(0.115)	(0.0793)	(0.0988)
Observations	419844	42222	45450	84588	244893
Mean of Y	39.59	36.44	30.74	44.88	40.17
SD	76.50	76.34	67.74	85.37	74.97

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. In this exercise, the real minimum wage is set to its previous value unless the real minimum wage increase between two years exceeds the national inflation rate between these years. I regress the number of employees working during a typical 8-hour workday on the real minimum wages and the interaction between these wages and the routineness and offshorability indexes. Each variable is further interacted with the type of employee, namely, contract workers and managers. Regular workers are the excluded type of employee. Column (1) reports the results for all firms. Columns (2)-(5) report the results for firms in the first-fourth compensation groups, respectively. For every district, industry, year, I compute the median compensation per day across firms for regular workers and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample. Columns (2)-(5) reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%, between 105 and 130%, between 130 and 180%, and above 180% of the average minimum wage in the district over the study period, respectively. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% of values of the dependent variable are winsorized. All firms with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table G.5: Total effect of a minimum wage increase on the number of employees working in a typical workday- variation from changes larger than the inflation

	(1) Pooled	(2) Group 1	(3) Group 2	(4) Group 3	(5) Group 4
Minimum wage	-.01	-.6**	-.05	-.1	.25***
	(.051)	(.281)	(.102)	(.092)	(.077)
MinXContract	.05	.51***	-.01	.13*	-.01
	(.038)	(.168)	(.071)	(.067)	(.046)
MinXManager	-.05**	.47***	-.1*	-.05	-.15***
	(.025)	(.126)	(.053)	(.041)	(.042)
MinXRTI	.5***	-.2	.35*	.7***	.51***
	(.133)	(.368)	(.205)	(.235)	(.164)
MinXRTIXContract	-.26***	.29	-.26*	-.24	-.31***
	(.084)	(.242)	(.143)	(.168)	(.109)
MinXRTIXManager	-.23***	.31*	-.3***	-.28**	-.32***
	(.063)	(.17)	(.111)	(.125)	(.084)
MinXOff	-.4***	-.86***	-.49*	-.53***	-.17
	(.123)	(.313)	(.254)	(.166)	(.178)
MinXOffXContract	.31***	.76***	.33*	.14	.3***
	(.082)	(.196)	(.176)	(.112)	(.118)
MinXOffXManager	.17***	.68***	.18	-.1	.14
	(.059)	(.161)	(.127)	(.089)	(.087)
Observations	419844	42222	45450	84588	244893
Mean of Y	39.59	36.44	30.74	44.88	40.17
SD	76.50	76.34	67.74	85.37	74.97

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. In this exercise, the real minimum wage is set to its previous value unless the real minimum wage increase between two years exceeds the national inflation rate between these years. I regress the number of employees working during a typical 8-hour workday on the real minimum wages and the interaction between these wages and the routineness and offshorability indexes. Each variable is further interacted with the type of employee, namely, contract workers and managers. Regular workers are the excluded type of employee. I compute the total effect of a typical real minimum wage increase of 2.5 rupee for each type of employee. Column (1) reports the results for all firms. Columns (2)-(5) report the results for firms in the first-fourth compensation groups, respectively. For every district, industry, year, I compute the median compensation per day across firms for regular workers and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample. Columns (2)-(5) reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%, between 105 and 130%, between 130 and 180%, and above 180% of the average minimum wage in the district over the study period, respectively. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% of values of the dependent variable are winsorized. All firms with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table G.6: Effect of a minimum wage increase on the number of mandays-variation from changes larger than the inflation

	(1) Pooled	(2) Group 1	(3) Group 2	(4) Group 3	(5) Group 4
Minimum wage	-1.286	-65.32**	-5.631	-13.23	28.42***
	(5.475)	(29.07)	(12.20)	(10.89)	(7.811)
MinXContract	4.981	116.0**	-0.878	24.83	-27.86**
	(8.958)	(45.58)	(18.57)	(17.18)	(11.48)
MinXManager	-3.577	111.4***	-8.482	5.707	-44.83***
	(7.546)	(40.59)	(16.27)	(14.44)	(10.88)
MinXRTI	57.99***	38.48**	45.96**	94.54***	29.91*
	(13.90)	(19.21)	(20.31)	(31.94)	(16.82)
MinXRTIXContract	-91.49***	-66.34**	-80.79***	-138.1***	-64.54**
	(22.63)	(27.57)	(29.53)	(51.75)	(26.10)
MinXRTIXManager	-80.59***	-61.33***	-76.88***	-123.6***	-50.27**
	(19.65)	(19.23)	(24.78)	(44.55)	(23.72)
MinXOff	-52.99***	-34.15*	-59.01**	-51.50***	-57.79***
	(14.81)	(18.02)	(28.48)	(19.44)	(22.33)
MinXOffXContract	86.66***	67.65***	103.2**	56.70**	97.50***
	(24.01)	(23.67)	(44.91)	(27.74)	(36.16)
MinXOffXManager	82.14***	62.76***	97.84**	50.22**	96.93***
	(21.21)	(21.45)	(39.58)	(24.94)	(30.14)
Observations	419844	42222	45450	84588	244893
Mean of Y	11690.0	9926.0	8950.9	13563.5	11929.5
SD	23067.7	21719.8	20604.9	26111.5	22634.2

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. In this exercise, the real minimum wage is set to its previous value unless the real minimum wage increase between two years exceeds the national inflation rate between these years. I regress the number of 8-hour workdays paid to each group of employee over the year on the real minimum wages and the interaction between these wages and the routineness and offshorability indexes. Each variable is further interacted with the type of employee, namely, contract workers and managers. Regular workers are the excluded type of employee. Column (1) reports the results for all firms. Columns (2)-(5) report the results for firms in the first-fourth compensation groups, respectively. For every district, industry, year, I compute the median compensation per day across firms for regular workers and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample. Columns (2)-(5) reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%, between 105 and 130%, between 130 and 180%, and above 180% of the average minimum wage in the district over the study period, respectively. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% of values of the dependent variable are winsorized. All firms with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table G.7: Total effect of a minimum wage increase on the number of mandays-variation from changes larger than the inflation

	(1) Pooled	(2) Group 1	(3) Group 2	(4) Group 3	(5) Group 4
Minimum wage	-3.21	-163.3**	-14.08	-33.07	71.05***
	(13.688)	(72.676)	(30.497)	(27.235)	(19.526)
MinXContract	9.24	126.74***	-16.27	29.01	1.41
	(9.724)	(45.114)	(20.078)	(18.56)	(12.163)
MinXManager	-12.16*	115.31***	-35.28**	-18.8	-41.02***
	(6.875)	(34.63)	(15.746)	(12.822)	(11.234)
MinXRTI	141.77***	-67.1	100.82	203.28***	145.83***
	(38.25)	(95.841)	(62.87)	(70.085)	(48.404)
MinXRTIXContract	-74.5***	57.09	-103.36***	-79.99	-85.16***
	(24.462)	(67.639)	(43.876)	(49.231)	(32.769)
MinXRTIXManager	-68.65***	58.18	-112.59***	-91.54***	-91.92***
	(18.539)	(48.372)	(35.364)	(37.06)	(25.062)
MinXOff	-135.68***	-248.69***	-161.61*	-161.82***	-73.42
	(38.058)	(82.852)	(83.2)	(50.557)	(52.151)
MinXOffXContract	93.43***	210.48***	94.2*	42	100.69***
	(25.046)	(52.933)	(55.908)	(32.302)	(35.082)
MinXOffXManager	60.73***	186.82***	61.78	-22	56.84**
	(18.446)	(44.362)	(42.137)	(26.38)	(25.046)
Observations	419844	42222	45450	84588	244893
Mean of Y	11690.0	9926.0	8950.9	13563.5	11929.5
SD	23067.7	21719.8	20604.9	26111.5	22634.2

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. In this exercise, the real minimum wage is set to its previous value unless the real minimum wage increase between two years exceeds the national inflation rate between these years. I regress the number of 8-hour workdays paid to each group of employee over the year on the real minimum wages and the interaction between these wages and the routineness and offshorability indexes. Each variable is further interacted with the type of employee, namely, contract workers and managers. Regular workers are the excluded type of employee. I compute the total effect of a typical real minimum wage increase of 2.5 rupee for each type of employee. Column (1) reports the results for all firms. Columns (2)-(5) report the results for firms in the first-fourth compensation groups, respectively. For every district, industry, year, I compute the median compensation per day across firms for regular workers and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample. Columns (2)-(5) reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%, between 105 and 130%, between 130 and 180%, and above 180% of the average minimum wage in the district over the study period, respectively. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% of values of the dependent variable are winsorized. All firms with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

H Robustness controlling for the outside option wage

Table H.1: Effect of a minimum wage increase on overall capital investment controlling for the outside option

	Capital			
	(1)	(2)	(3)	(4)
Minimum wage	-0.00807	-0.0722	-0.00224	-0.0697
	(0.0485)	(0.0524)	(0.0526)	(0.0512)
Minimum wage X RTI		0.284**		0.352**
		(0.130)		(0.147)
Minimum wage X Offshore			-0.0509	-0.155
			(0.122)	(0.128)
Observations	54997	54997	54997	54997
Mean of Y	12.29	12.29	12.29	12.29
SD	68.30	68.30	68.30	68.30

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress investment on real minimum wages in column (1). I also include the interaction between the real minimum wages and the routineness index in column (2). In column (3), I include the interaction between the real minimum wages and the index of offshorability. Column (4) is the prefered specification and includes both interactions. In all specifications, I control for the average real minimum wage in other industries with a statutory minimum wage and its interactions with the routineness and offshorability indexes. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. All specifications include fourth-degree polynomials in age, lagged revenue, lagged profit margin, and revenue growth. Standard errors are clustered at the four-digit-industry-by-state level. The largest 2.5% and smallest 1% of values of the dependent variable are winsorized. All firms with positive net value in machinery and/or computers for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table H.2: Effect of a minimum wage increase on investment in machinery controlling for the outside option

	Machinery			
	(1)	(2)	(3)	(4)
Minimum wage	-0.0155	-0.0603	-0.0108	-0.0585
	(0.0418)	(0.0451)	(0.0443)	(0.0440)
Minimum wage X RTI		0.198*		0.249**
		(0.112)		(0.126)
Minimum wage X Offshore			-0.0412	-0.115
			(0.101)	(0.108)
Observations	54997	54997	54997	54997
Mean of Y	7.761	7.761	7.761	7.761
SD	49.27	49.27	49.27	49.27

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress machinery investment on real minimum wages in column (1). I also include the interaction between the real minimum wages and the routineness index in column (2). In column (3), I include the interaction between the real minimum wages and the index of offshorability. Column (4) is the prefered specification and includes both interactions. In all specifications, I control for the average real minimum wage in other industries with a statutory minimum wage and its interactions with the routineness and offshorability indexes. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. All specifications include fourth-degree polynomials in age, lagged revenue, lagged profit margin, and revenue growth. Standard errors are clustered at the four-digit-industry-by-state level. The largest 2.5% and smallest 1% of values of the dependent variable are winsorized. All firms with positive net value in machinery and/or computers for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table H.3: Effect of a minimum wage increase on investment in computers controlling for the outside option

	Computers			
	(1)	(2)	(3)	(4)
Minimum wage	-0.0310	-0.0598	-0.0117	-0.0560
	(0.0359)	(0.0480)	(0.0370)	(0.0463)
Minimum wage X RTI		0.127		0.231
		(0.140)		(0.147)
Minimum wage X Offshore			-0.169*	-0.237***
			(0.0903)	(0.0901)
Observations	54997	54997	54997	54997
Mean of Y	8.332	8.332	8.332	8.332
SD	66.00	66.00	66.00	66.00

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress computer investment on real minimum wages in column (1). I also include the interaction between the real minimum wages and the routineness index in column (2). In column (3), I include the interaction between the real minimum wages and the index of offshorability. Column (4) is the prefered specification and includes both interactions. In all specifications, I control for the average real minimum wage in other industries with a statutory minimum wage and its interactions with the routineness and offshorability indexes. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. All specifications include fourth-degree polynomials in age, lagged revenue, lagged profit margin, and revenue growth. Standard errors are clustered at the four-digit-industry-by-state level. The largest 2.5% and smallest 1% of values of the dependent variable are winsorized. All firms with positive net value in machinery and/or computers for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table H.4: Effect of a minimum wage increase on the number of employees working in a typical workday controlling for the outside option

	(1) Pooled	(2) Group 1	(3) Group 2	(4) Group 3	(5) Group 4
Minimum wage	-0.0138	-0.318***	-0.0617*	-0.0526	0.114***
	(0.0208)	(0.101)	(0.0355)	(0.0362)	(0.0325)
MinXContract	0.0368	0.536***	0.0975*	0.0988	-0.118**
	(0.0356)	(0.159)	(0.0568)	(0.0620)	(0.0492)
MinXManager	-0.00273	0.492***	0.0657	0.0228	-0.172***
	(0.0279)	(0.143)	(0.0455)	(0.0478)	(0.0466)
MinXRTI	0.193***	0.132**	0.184***	0.307**	0.0878
	(0.0508)	(0.0636)	(0.0611)	(0.119)	(0.0592)
MinXRTIXContract	-0.325***	-0.236**	-0.251***	-0.488***	-0.210**
	(0.0830)	(0.0978)	(0.0968)	(0.188)	(0.0936)
MinXRTIXManager	-0.278***	-0.213***	-0.231***	-0.432***	-0.163*
	(0.0701)	(0.0695)	(0.0727)	(0.158)	(0.0853)
MinXOff	-0.164***	-0.159***	-0.253***	-0.123**	-0.209***
	(0.0474)	(0.0611)	(0.0838)	(0.0592)	(0.0705)
MinXOffXContract	0.302***	0.218***	0.345**	0.193**	0.362***
	(0.0762)	(0.0767)	(0.136)	(0.0974)	(0.117)
MinXOffXManager	0.279***	0.201***	0.322***	0.165*	0.349***
	(0.0675)	(0.0702)	(0.116)	(0.0868)	(0.0991)
Observations	420051	42270	45483	84618	244998
Mean of Y	39.27	36.44	30.73	44.80	39.69
SD	76.33	76.33	67.79	85.46	74.59

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress the number of employees working during a typical 8-hour workday on the real minimum wages and the interaction between these wages and the routineness and offshorability indexes. Each variable is further interacted with the type of employee, namely, contract workers and managers. Regular workers are the excluded type of employee. I compute the total effect of a typical real minimum wage increase of 2.5 rupee for each type of employee. Column (1) reports the results for all firms. Columns (2)-(5) report the results for firms in the first-fourth compensation groups, respectively. For every district, industry, year, I compute the median compensation per day across firms for regular workers and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample. Columns (2)-(5) reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%, between 105 and 130%, between 130 and 180%, and above 180% of the average minimum wage in the district over the study period, respectively. In all specifications, I control for the average real minimum wage in other industries with a statutory minimum wage and its interactions with the routineness and offshorability indexes. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% of values of the dependent variable are winsorized. All firms with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table H.5: Total effect of a minimum wage increase on the number of employees working in a typical workday controlling for the outside option

	(1) Pooled	(2) Group 1	(3) Group 2	(4) Group 3	(5) Group 4
Minimum wage	-.03	-.8***	-.15*	-.13	.29***
	(.052)	(.252)	(.089)	(.09)	(.081)
MinXContract	.06	.54***	.09	.12	-.01
	(.04)	(.155)	(.063)	(.071)	(.048)
MinXManager	-.04*	.44***	.01	-.07*	-.14***
	(.025)	(.118)	(.043)	(.043)	(.043)
MinXRTI	.45***	-.46*	.31*	.63***	.51***
	(.135)	(.258)	(.17)	(.271)	(.164)
MinXRTIXContract	-.27***	.29	-.08	-.34**	-.31***
	(.082)	(.185)	(.129)	(.153)	(.106)
MinXRTIXManager	-.25***	.23*	-.11	-.39***	-.33***
	(.063)	(.138)	(.087)	(.107)	(.084)
MinXOff	-.44***	-1.19***	-.79***	-.44***	-.24
	(.124)	(.265)	(.214)	(.163)	(.181)
MinXOffXContract	.4***	.69***	.32**	.29***	.37***
	(.081)	(.186)	(.154)	(.122)	(.118)
MinXOffXManager	.25***	.54***	.18*	.03	.2***
	(.059)	(.164)	(.104)	(.086)	(.087)
Observations	420051	42270	45483	84618	244998
Mean of Y	39.27	36.44	30.73	44.80	39.69
SD	76.33	76.33	67.79	85.46	74.59

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress the number of employees working during a typical 8-hour workday on the real minimum wages and the interaction between these wages and the routineness and offshorability indexes. Each variable is further interacted with the type of employee, namely, contract workers and managers. Regular workers are the excluded type of employee. I compute the total effect of a typical real minimum wage increase of 2.5 rupee for each type of employee. Column (1) reports the results for all firms. Columns (2)-(5) report the results for firms in the first-fourth compensation groups, respectively. For every district, industry, year, I compute the median compensation per day across firms for regular workers and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample. Columns (2)-(5) reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%, between 105 and 130%, between 130 and 180%, and above 180% of the average minimum wage in the district over the study period, respectively. In all specifications, I control for the average real minimum wage in other industries with a statutory minimum wage and its interactions with the routineness and offshorability indexes. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% of values of the dependent variable are winsorized. All firms with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table H.6: Effect of a minimum wage increase on the number of mandays controlling for the outside option

	(1) Pooled	(2) Group 1	(3) Group 2	(4) Group 3	(5) Group 4
Minimum wage	-3.665	-78.85***	-13.01	-15.65	31.84***
	(5.592)	(23.57)	(10.48)	(10.71)	(8.028)
MinXContract	8.427	133.9***	21.75	26.29	-31.52***
	(9.215)	(37.49)	(16.11)	(17.46)	(11.96)
MinXManager	0.152	122.5***	16.43	6.558	-47.62***
	(7.655)	(33.72)	(13.65)	(14.58)	(11.49)
MinXRTI	56.35***	26.30	59.37***	91.32**	25.69
	(14.98)	(17.22)	(19.63)	(35.52)	(17.36)
MinXRTIXContract	-92.70***	-64.06**	-77.31***	-144.1***	-61.35**
	(24.02)	(26.16)	(29.92)	(55.70)	(27.11)
MinXRTIXManager	-82.46***	-59.14***	-74.28***	-130.0***	-48.62*
	(20.83)	(17.22)	(24.64)	(47.86)	(25.10)
MinXOff	-54.51***	-51.49***	-90.14***	-36.51*	-69.14***
	(15.61)	(19.51)	(28.57)	(18.71)	(21.93)
MinXOffXContract	98.68***	72.52***	114.9**	62.33**	118.7***
	(24.94)	(23.59)	(46.02)	(30.44)	(35.69)
MinXOffXManager	92.85***	67.02***	108.7***	55.03**	115.6***
	(22.14)	(21.66)	(40.27)	(27.31)	(30.09)
Observations	420051	42270	45483	84618	244998
Mean of Y	11602.8	9922.0	8951.1	13548.3	11802.5
SD	23016.8	21712.3	20619.7	26144.8	22524.9

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress the number of 8-hour workdays paid to each group of employee over the year on the real minimum wages and the interaction between these wages and the routineness and offshorability indexes. Each variable is further interacted with the type of employee, namely, contract workers and managers. Regular workers are the excluded type of employee. I compute the total effect of a typical real minimum wage increase of 2.5 rupee for each type of employee. Column (1) reports the results for all firms. Columns (2)-(5) report the results for firms in the first-fourth compensation groups, respectively. For every district, industry, year, I compute the median compensation per day across firms for regular workers and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample. Columns (2)-(5) reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%, between 105 and 130%, between 130 and 180%, and above 180% of the average minimum wage in the district over the study period, respectively. In all specifications, I control for the average real minimum wage in other industries with a statutory minimum wage and its interactions with the routineness and offshorability indexes. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% of values of the dependent variable are winsorized. All firms with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table H.7: Total effect of a minimum wage increase on the number of mandays controlling for the outside option

	(1) Pooled	(2) Group 1	(3) Group 2	(4) Group 3	(5) Group 4
Minimum wage	-9.16	-197.12***	-32.52	-39.13	79.61***
	(13.98)	(58.93)	(26.212)	(26.783)	(20.07)
MinXContract	11.9	137.55***	21.85	26.59	.8
	(9.998)	(38.775)	(16.753)	(19.049)	(12.318)
MinXManager	-8.78	109.25***	8.55	-22.73*	-39.44***
	(6.894)	(29.851)	(12.903)	(13.126)	(11.209)
MinXRTI	131.73***	-131.37*	115.91**	189.16***	143.83***
	(40.279)	(68.705)	(53.562)	(80.945)	(48.04)
MinXRTIXContract	-78.96***	43.16	-22.99	-105.25**	-88.37***
	(23.938)	(52.639)	(37.939)	(45.584)	(31.314)
MinXRTIXManager	-74.05***	27.14	-28.72	-119.4***	-96.78***
	(18.37)	(39.535)	(27.552)	(32.937)	(24.432)
MinXOff	-145.45***	-325.84***	-257.88***	-130.39***	-93.24*
	(38.919)	(70.514)	(72.724)	(51.144)	(52.412)
MinXOffXContract	122.31***	190.12***	83.79*	91.14***	124.66***
	(24.502)	(52.926)	(49.078)	(35.545)	(34.167)
MinXOffXManager	87.07***	148.09***	54.99	23.59	76.66***
	(18.12)	(47.516)	(35.398)	(26.618)	(24.198)
Observations	420051	42270	45483	84618	244998
Mean of Y	11602.8	9922.0	8951.1	13548.3	11802.5
SD	23016.8	21712.3	20619.7	26144.8	22524.9

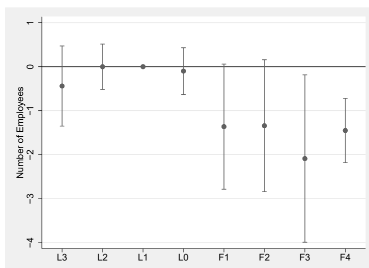
Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress the number of 8-hour workdays paid to each group of employee over the year on the real minimum wages and the interaction between these wages and the routineness and offshorability indexes. Each variable is further interacted with the type of employee, namely, contract workers and managers. Regular workers are the excluded type of employee. I compute the total effect of a typical real minimum wage increase of 2.5 rupee for each type of employee. Column (1) reports the results for all firms. Columns (2)-(5) report the results for firms in the first-fourth compensation groups, respectively. For every district, industry, year, I compute the median compensation per day across firms for regular workers and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample. Columns (2)-(5) reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%, between 105 and 130%, between 130 and 180%, and above 180% of the average minimum wage in the district over the study period, respectively. In all specifications, I control for the average real minimum wage in other industries with a statutory minimum wage and its interactions with the routineness and offshorability indexes. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% of values of the dependent variable are winsorized. All firms with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

I Distributed lag regression for the number of employees working in a typical workday

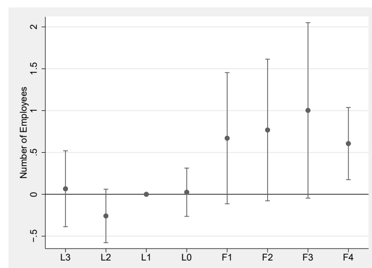
Group 1: ≤105% of minimum wage

Figure I.1: Firms in the average industry

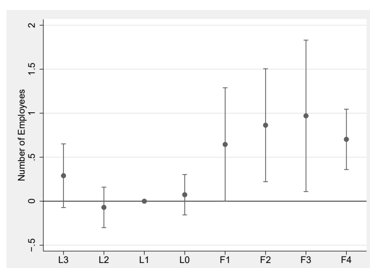
(a) Regular workers



(b) Contract workers



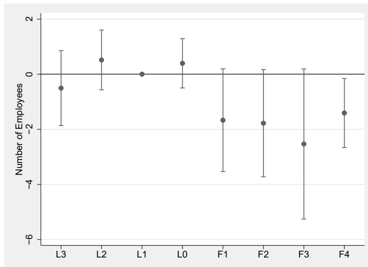
(c) Managers



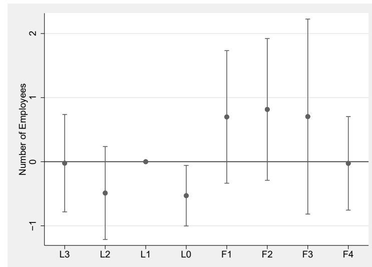
Note: 90% confidence bands are displayed. I report the coefficients of the event-study regression for a typical minimum wage hike (2.5 rupees). In the first figure of this subsection, I show the results when the routineness and offshorability indexes are at the mean (when they are equal to 0). In the second figure, I report the results when the routineness intensity index is one SD above the mean (the offshorability index is kept at the mean). In the last, I report the results when the offshorability intensity index is one SD above the mean (the routineness index is kept at the mean). In each figure, I report the results for regular workers in Panel (a), for contract worekers in Panel (b), and for managers in Panel (c). This subsection reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% of values of the dependent variable are winsorized. All firms with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Figure I.2: Firms in routine industries

(a) Regular workers



(b) Contract workers



(c) Managers

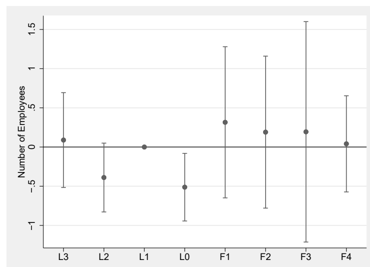
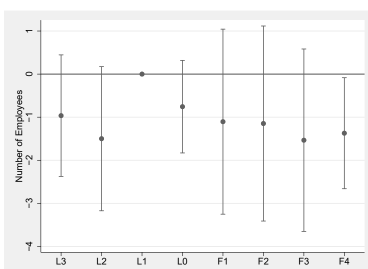
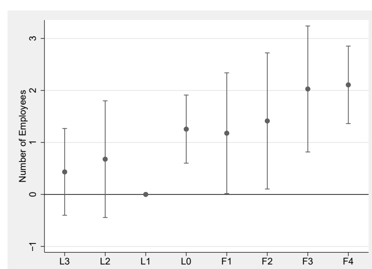


Figure I.3: Firms in offshorable industries

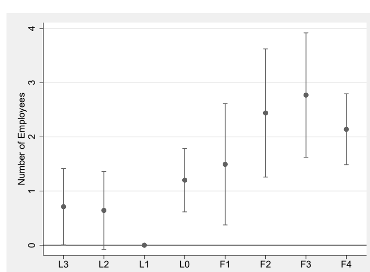
(a) Regular workers



(b) Contract workers



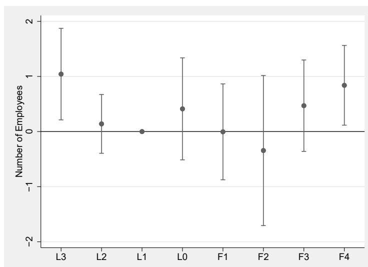
(c) Managers



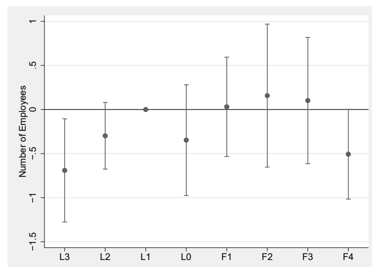
Group 2: 105-130% of minimum wage

Figure I.4: Firms in the average industry

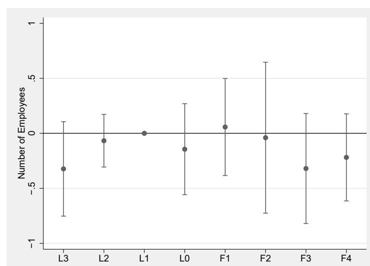
(a) Regular workers



(b) Contract workers



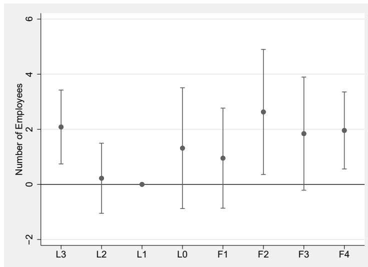
(c) Managers



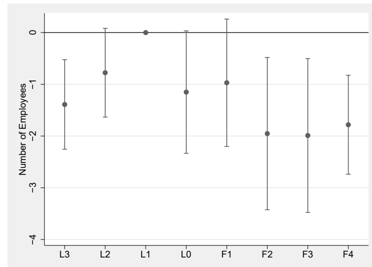
Note: 90% confidence bands are displayed. I report the coefficients of the event-study regression for a typical minimum wage hike (2.5 rupees). In the first figure of this subsection, I show the results when the routineness and offshorability indexes are at the mean (when they are equal to 0). In the second figure, I report the results when the routineness intensity index is one SD above the mean (the offshorability index is kept at the mean). In the last, I report the results when the offshorability intensity index is one SD above the mean (the routineness index is kept at the mean). In each figure, I report the results for regular workers in Panel (a), for contract worekers in Panel (b), and for managers in Panel (c). This subsection reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is between 105% and 130%. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% of values of the dependent variable are winsorized. All firms with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Figure I.5: Firms in routine industries

(a) Regular workers



(b) Contract workers



(c) Managers

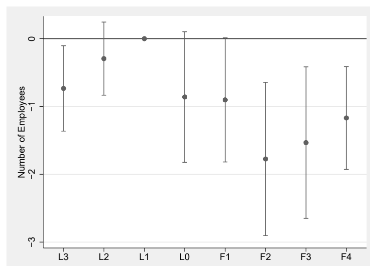
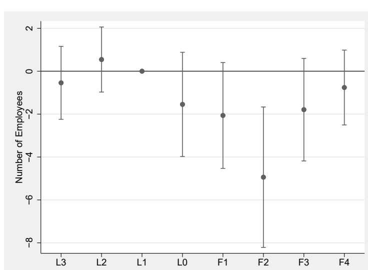
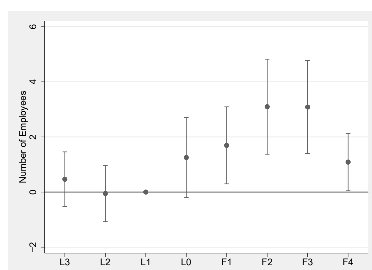


Figure I.6: Firms in offshorable industries

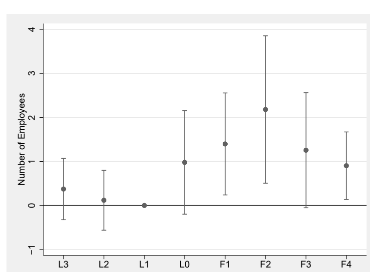
(a) Regular workers



(b) Contract workers



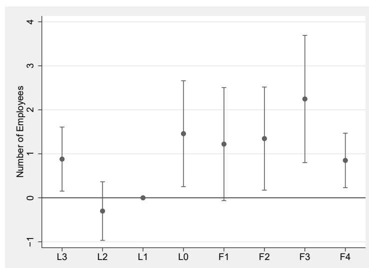
(c) Managers



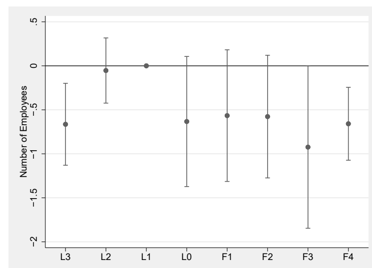
Group 3: 130-180% of minimum wage

Figure I.7: Firms in the average industry

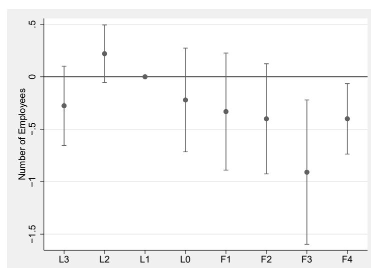
(a) Regular workers



(b) Contract workers



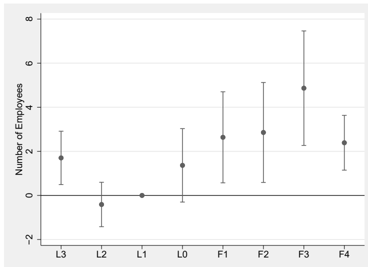
(c) Managers



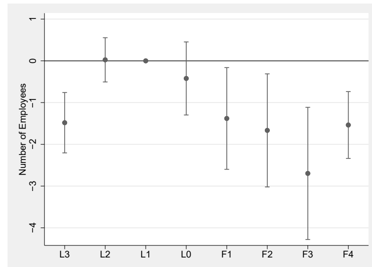
Note: 90% confidence bands are displayed. I report the coefficients of the event-study regression for a typical minimum wage hike (2.5 rupees). In the first figure of this subsection, I show the results when the routineness and offshorability indexes are at the mean (when they are equal to 0). In the second figure, I report the results when the routineness intensity index is one SD above the mean (the offshorability index is kept at the mean). In the last, I report the results when the offshorability intensity index is one SD above the mean (the routineness index is kept at the mean). In each figure, I report the results for regular workers in Panel (a), for contract worekers in Panel (b), and for managers in Panel (c). This subsection reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is between 130% and 180%. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% of values of the dependent variable are winsorized. All firms with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Figure I.8: Firms in routine industries

(a) Regular workers



(b) Contract workers



(c) Managers

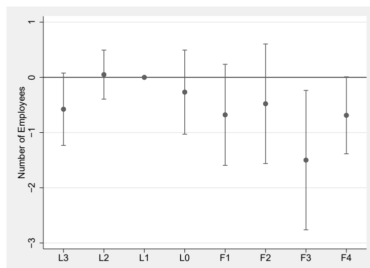
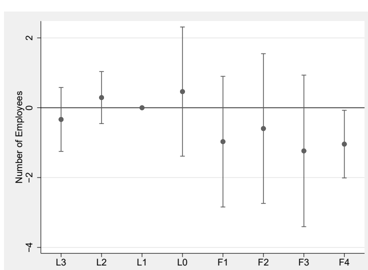
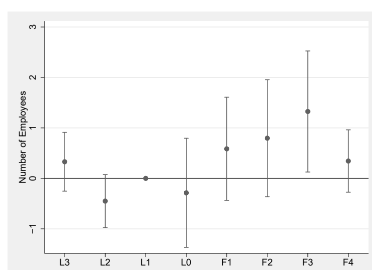


Figure I.9: Firms in offshorable industries

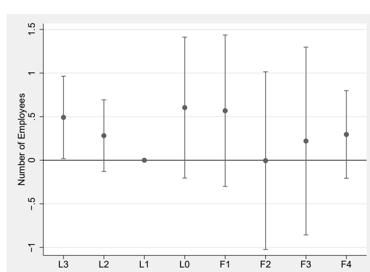
(a) Regular workers



(b) Contract workers



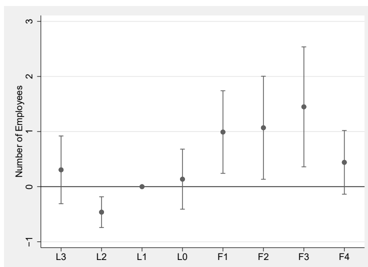
(c) Managers



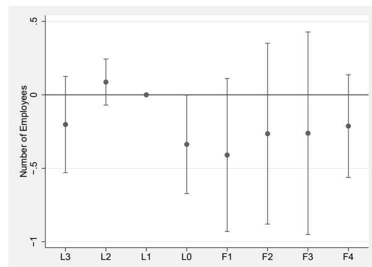
Group 4: >180% of minimum wage

Figure I.10: Firms in the average industry

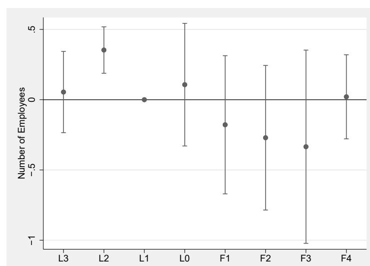
(a) Regular workers



(b) Contract workers



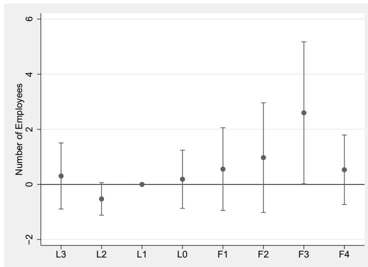
(c) Managers



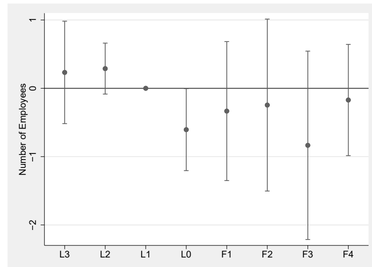
Note: 90% confidence bands are displayed. I report the coefficients of the event-study regression for a typical minimum wage hike (2.5 rupees). In the first figure of this subsection, I show the results when the routineness and offshorability indexes are at the mean (when they are equal to 0). In the second figure, I report the results when the routineness intensity index is one SD above the mean (the offshorability index is kept at the mean). In the last, I report the results when the offshorability intensity index is one SD above the mean (the routineness index is kept at the mean). In each figure, I report the results for regular workers in Panel (a), for contract worekers in Panel (b), and for managers in Panel (c). This subsection reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is greater than 180%. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% of values of the dependent variable are winsorized. All firms with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Figure I.11: Firms in routine industries

(a) Regular workers



(b) Contract workers



(c) Managers

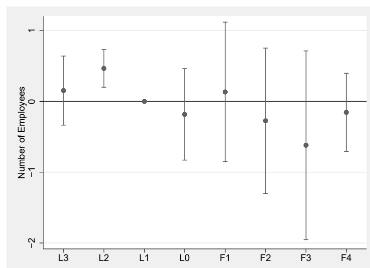
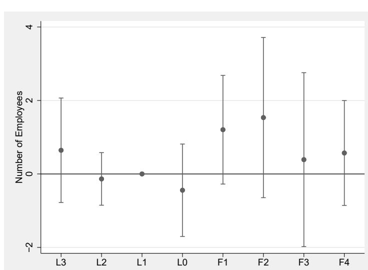
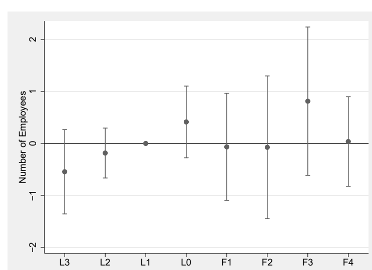


Figure I.12: Firms in offshorable industries

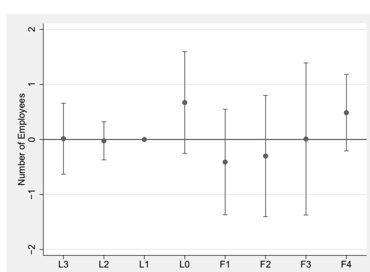
(a) Regular workers



(b) Contract workers



(c) Managers



J Aggregate employment

Table J.1: Effect of a minimum wage increase on aggregate employment (in logs) using household survey data

	(1) Pooled	(2) 14-24 years old	(3) 25-32 years old	(4) 33-43 years old	(5) 44-65 years old
Minimum wage	-0.000282	-0.00115**	-0.000157	-0.000217	0.000345
	(0.000245)	(0.000498)	(0.000479)	(0.000486)	(0.000531)
Minimum wage X RTI	-0.000285	0.0000226	0.000723	-0.000667	-0.00146*
	(0.000392)	(0.000781)	(0.000772)	(0.000795)	(0.000836)
Minimum wage X Offshore	-0.000437	-0.000101	-0.000740	0.000168	-0.000803
	(0.000376)	(0.000791)	(0.000749)	(0.000736)	(0.000769)
Observations	92872	19915	24207	25171	23498
Mean of Y	7.664	7.736	7.624	7.682	7.626
SD	1.732	1.737	1.750	1.715	1.725

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. India's National Sample Survey collects data on employment for individuals in the 14-65 age range every five years or so. The 2000, 2005, and 2008 waves contain employment data. I aggregate employment at the state, district, four-digit industry, and age quartile level. In doing so, I use the sample weights provided in the survey waves. I regress the log aggregate employment on the real minimum wages as well as the interactions between the minimum wages and the routineness and offshorability indexes in Column (1). I include fixed effects for the age quartile in that column only. In Column (2) to (5), I run the same regression for each age quartile separately. All specifications include district, year, and four-digit-industry fixed effects. I report White standard errors in parenthesis. The largest 5% of values of aggregate employment are winsorized. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The minimum wage data spans from 2002-2008. When merging in the wage data, I attribute the 2002 wages to the 2000 employment wave. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table J.2: Effect of a minimum wage increase on aggregate employment (in logs) controlling for the average minimum wage across other states

	(1) Pooled	(2) 14-24 years old	(3) 25-32 years old	(4) 33-43 years old	(5) 44-65 years old
Minimum wage	-0.000358	-0.00125**	-0.000384	-0.000362	0.000152
	(0.000263)	(0.000535)	(0.000511)	(0.000644)	(0.000582)
Minimum wage X RTI	-0.000221	-0.000150	0.000994	0.000120	-0.00134
	(0.000436)	(0.000868)	(0.000848)	(0.00100)	(0.000959)
Minimum wage X Offshore	-0.000538	-0.000323	-0.000469	0.000396	-0.00144
	(0.000429)	(0.000892)	(0.000851)	(0.000877)	(0.000899)
Minwage other	-0.000225	-0.000503	-0.00106	0.0000931	-0.00149
	(0.000678)	(0.00136)	(0.00123)	(0.00307)	(0.00164)
Minwage other X RTI	0.000629	-0.00139	0.000369	0.00610	0.00191
	(0.00157)	(0.00313)	(0.00283)	(0.00538)	(0.00391)
Minwage other X Offshore	-0.00158	-0.00236	0.00324	0.00227	-0.00842
	(0.00264)	(0.00519)	(0.00496)	(0.00630)	(0.00607)
Observations	90511	19362	23602	24558	22906
Mean of Y	7.664	7.736	7.624	7.682	7.626
SD	1.732	1.737	1.750	1.715	1.725

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. India's National Sample Survey collects data on employment for individuals in the 14-65 age range every five years or so. The 2000, 2005, and 2008 waves contain employment data. I aggregate employment at the state, district, four-digit industry, and age quartile level. In doing so, I use the sample weights provided in the survey waves. I regress the log aggregate employment on the real minimum wages as well as the interactions between the minimum wages and the routineness and offshorability indexes in Column (1). I include fixed effects for the age quartile in that column only. In Column (2) to (5), I run the same regression for each age quartile separately. All specifications include district, year, and four-digit-industry fixed effects. I also include the average minimum wage in the same industry across other states and its interaction with the routineness and offshorability measures in all specifications. I report White standard errors in parenthesis. The largest 5% of values of aggregate employment are winsorized. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The minimum wage data spans from 2002-2008. When merging in the wage data, I attribute the 2002 wages to the 2000 employment wave. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

K Layoff regulations intensity

Table K.1: Effect of a minimum wage increase on overall capital investment using variation from pro-employer and neutral states

	Capital			
	(1)	(2)	(3)	(4)
Minimum wage	0.0904	0.0129	0.116	0.0355
	(0.116)	(0.144)	(0.120)	(0.144)
Minimum wage X RTI		0.390		0.525
		(0.354)		(0.346)
Minimum wage X Offshore			-0.138	-0.266
			(0.219)	(0.197)
Observations	11813	11813	11813	11813
Mean of Y	11.31	11.31	11.31	11.31
SD	66.30	66.30	66.30	66.30

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. In this exercise, I keep observations in pro-employer and neutral states only. I regress investment on real minimum wages in Column (1). I also include the interaction between the real minimum wages and the routineness index in Column (2). In Column (3), I include the interaction between the real minimum wages and the index of offshorability. Column (4) is the preferred specification and includes both interactions. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. All specifications include fourth-degree polynomials in age, lagged revenue, lagged profit margin, and revenue growth. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% and smallest 1% of values of the dependent variable are winsorized. All firms with positive net value in machinery and/or computers for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table K.2: Effect of a minimum wage increase on overall capital investment using variation from pro-worker states

	Capital			
	(1)	(2)	(3)	(4)
Minimum wage	0.0599	-0.00329	0.0670	0.00109
	(0.0616)	(0.0861)	(0.0645)	(0.0866)
Minimum wage X RTI		0.262		0.278
		(0.281)		(0.284)
Minimum wage X Offshore			0.166	0.190
			(0.391)	(0.390)
Observations	26101	26101	26101	26101
Mean of Y	12.01	12.01	12.01	12.01
SD	68.99	68.99	68.99	68.99

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. In this exercise, I keep observations in pro-worker states only. I regress investment on real minimum wages in Column (1). I also include the interaction between the real minimum wages and the routineness index in Column (2). In Column (3), I include the interaction between the real minimum wages and the index of offshorability. Column (4) is the preferred specification and includes both interactions. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. All specifications include fourth-degree polynomials in age, lagged revenue, lagged profit margin, and revenue growth. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% and smallest 1% of values of the dependent variable are winsorized. All firms with positive net value in machinery and/or computers for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table K.3: Total effect of a minimum wage increase on the number of employees working in a typical workday using variation form pro-employer states

	(1) Pooled	(2) Group 1	(3) Group 2	(4) Group 3	(5) Group 4
Minimum wage	.05	-1***	-.28	.09	.35***
	(.085)	(.337)	(.326)	(.168)	(.121)
MinXContract	.03	.7***	.36*	.15	-.08
	(.053)	(.175)	(.215)	(.111)	(.074)
MinXManager	-.02	.58***	.15	-.02	-.2***
	(.042)	(.176)	(.191)	(.105)	(.059)
MinXRTI	.59**	-.69**	.87***	1.53**	.53**
	(.259)	(.35)	(.331)	(.758)	(.247)
MinXRTIXContract	-.35***	.62***	.69***	-.87***	-.47***
	(.148)	(.223)	(.265)	(.348)	(.138)
MinXRTIXManager	-.35***	.32	.51**	-.66***	-.48***
	(.114)	(.223)	(.231)	(.242)	(.131)
MinXOff	-.49***	-1.48***	-1.86***	-.09	-.3
	(.198)	(.38)	(.384)	(.366)	(.211)
MinXOffXContract	.4***	.8***	-.03	.25	.36***
	(.12)	(.252)	(.277)	(.237)	(.134)
MinXOffXManager	.29***	.69***	-.31	.08	.15
	(.091)	(.262)	(.267)	(.197)	(.107)
Observations	163281	26907	12021	33066	90693
Mean of Y	43.764	40.686	42.386	51.237	42.32
SD	83.649	83.523	86.328	95.675	78.51

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. In this exercise, I keep observations in pro-employer states only. I regress the number of employees working during a typical 8-hour workday on the real minimum wages and the interaction between these wages and the routineness and offshorability indexes. Each variable is further interacted with the type of employee, namely, contract workers and managers. Regular workers are the excluded type of employee. I compute the total effect of a typical real minimum wage increase of 2.5 rupee for each type of employee. Column (1) reports the results for all firms. Columns (2)-(5) report the results for firms in the first-fourth compensation groups, respectively. For every district, industry, year, I compute the median compensation per day across firms for regular workers and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample. Columns (2)-(5) reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%, between 105 and 130%, between 130 and 180%, and above 180% of the average minimum wage in the district over the study period, respectively. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% of values of the dependent variable are winsorized. All firms with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table K.4: Total effect of a minimum wage increase on the number of employees working in a typical workday using variation from neutral states

	(1) Pooled	(2) Group 1	(3) Group 2	(4) Group 3	(5) Group 4
Minimum wage	-.27*	-.89*	-.23***	-.21	.13
	(.156)	(.524)	(.094)	(.138)	(.315)
MinXContract	.22**	.68*	.07	.09	-.06
	(.105)	(.359)	(.086)	(.124)	(.208)
MinXManager	-.03	.34	-.06	-.16***	-.4*
	(.071)	(.217)	(.055)	(.059)	(.206)
MinXRTI	.08	-.45	0	.22	.42
	(.199)	(.592)	(.175)	(.198)	(.485)
MinXRTIXContract	-.01	.39	.1	-.09	.12
	(.124)	(.537)	(.16)	(.158)	(.306)
MinXRTIXManager	-.12	.7***	-.05	-.36***	-.24
	(.09)	(.286)	(.105)	(.144)	(.28)
MinXOff	-.47**	-.82	-.5***	-.49**	.14
	(.202)	(.502)	(.15)	(.229)	(.514)
MinXOffXContract	.49***	.91***	.08	.29*	.07
	(.138)	(.387)	(.163)	(.172)	(.301)
MinXOffXManager	.09	.42*	-.04	-.16	-.39
	(.098)	(.254)	(.126)	(.11)	(.296)
Observations	94446	9492	19659	29844	34266
Mean of Y	36.919	33.802	27.009	39.439	41.856
SD	72.629	63.311	59.829	77.624	77.368

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. In this exercise, I keep observations in neutral states only. I regress the number of employees working during a typical 8-hour workday on the real minimum wages and the interaction between these wages and the routineness and offshorability indexes. Each variable is further interacted with the type of employee, namely, contract workers and managers. Regular workers are the excluded type of employee. I compute the total effect of a typical real minimum wage increase of 2.5 rupee for each type of employee. Column (1) reports the results for all firms. Columns (2)-(5) report the results for firms in the first-fourth compensation groups, respectively. For every district, industry, year, I compute the median compensation per day across firms for regular workers and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample. Columns (2)-(5) reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%, between 105 and 130%, between 130 and 180%, and above 180% of the average minimum wage in the district over the study period, respectively. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% of values of the dependent variable are winsorized. All firms with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

Table K.5: Total effect of a minimum wage increase on the number of employees working in a typical workday using variation from pro-worker states

	(1) Pooled	(2) Group 1	(3) Group 2	(4) Group 3	(5) Group 4
Minimum wage	.02	.39	.21	.13	.2*
	(.077)	(.97)	(.364)	(.125)	(.116)
MinXContract	0	.09	.29	-.03	.04
	(.055)	(.99)	(.32)	(.092)	(.071)
MinXManager	-.07*	.7	.3	-.15*	-.07
	(.04)	(.96)	(.335)	(.087)	(.062)
MinXRTI	.29**	-.67	2.08**	.64***	.61***
	(.143)	(.74)	(1.05)	(.256)	(.229)
MinXRTIXContract	-.21***	-1.2	1.5	-.02	-.03
	(.077)	(.86)	(.992)	(.184)	(.155)
MinXRTIXManager	-.2***	-.59	1.62	-.11	-.01
	(.075)	(.803)	(1.014)	(.19)	(.109)
MinXOff	-.39*	2.65***	-1.24	-.55**	-.46
	(.199)	(.995)	(.922)	(.256)	(.319)
MinXOffXContract	.42***	2.82***	-.41	.06	.19
	(.102)	(1.013)	(.922)	(.175)	(.203)
MinXOffXManager	.37***	3.37***	-.37	-.08	.12
	(.091)	(.992)	(.887)	(.153)	(.143)
Observations	113634	4008	8259	17160	83781
Mean of Y	44.871	23.858	29.078	48.615	46.819
SD	78.524	59.652	60.307	83.591	79.625

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. In this exercise, I keep observations in pro-worker and neutral states only. I regress the number of employees working during a typical 8-hour workday on the real minimum wages and the interaction between these wages and the routineness and offshorability indexes. Each variable is further interacted with the type of employee, namely, contract workers and managers. Regular workers are the excluded type of employee. I compute the total effect of a typical real minimum wage increase of 2.5 rupee for each type of employee. Column (1) reports the results for all firms. Columns (2)-(5) report the results for firms in the first-fourth compensation groups, respectively. For every district, industry, year, I compute the median compensation per day across firms for regular workers and average it across years. Then, I compute the ratio of the median compensation for regular workers across firms to the average minimum wage prevailing in the district over the study sample. Columns (2)-(5) reports the results of the regression for firms in districts where the median firm-level compensation paid to regular workers is less than 105%, between 105 and 130%, between 130 and 180%, and above 180% of the average minimum wage in the district over the study period, respectively. All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. Standard errors are clustered at the four-digit-industry-by-state level. The largest 5% of values of the dependent variable are winsorized. All firms with a positive number of employee for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

L Outsourcing

I compute the firms expenditure on outsourced work and services. This includes expenditures for intermediary goods produced by other firms, outsourced software development, outsourced consulting, etc. I exclude outsourcing expenditures related to audits, and any legal charges. I compute the growth rate in expenditure like the investment variables. I divide the change in expenditure over the year by the expenditure of the previous year. The latter is captured by the average between the end-of-year and beginning-of-year expenditure of the previous year.

Table L.1: Outsourcing growth

	Growth in outsourcing expenditure	
	(1)	(2)
Minimum wage	0.0323	0.00837
	(0.0580)	(0.0918)
Minimum wage X RTI		0.242
		(0.266)
Minimum wage X Offshore		-0.276
		(0.200)
Observations	54997	54997
Mean of Y	8.601	8.601
SD	81.95	81.95

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. I regress the growth in offshring expenditures in percent on real minimum wages in Column (1). I also include the interaction between the real minimum wages and the routineness index and the interaction between the real minimum wages and the index of offshorability in Column (2). All specifications include firm, district-by-year, and four-digit-industry-by-year fixed effects. All specifications include fourth-degree polynomials in age, lagged revenue, lagged profit margin, and revenue growth. Standard errors are clustered at the four-digit-industry-by-state level. The largest and smallest 5% of values of the dependent variable are winsorized. All firms with positive net value in machinery and/or computers and report outsourcing spending for any number of year during the study period are included in the analysis. Real minimum wages are obtained by deflating the nominal minimum wages by the national CPI index of that year. When no statutory minimum wages exist, the real minimum wage is set to 0. The routineness and offshorability indexes are computed at the industry level and measured in standard deviations from the average level of routineness and offshorability across all industries prior to the study sample.

M Proof of Propositions 1 and 2

M.1 Proposition 1

PROPOSITION 1: *Suppose that tasks are perfect complements, but inputs are not ($\sigma = 0$ and $\varepsilon_i > 0$ $\forall i$). In any given task, the demand will increase for the input that experiences the smallest percentage increase in wage. On the* *other hand, the demand for the input with the largest percentage increase in wage will decrease.*

When $\sigma = 0$, Equation (8) becomes:

$$d\mathcal{L}_j(i) = \varepsilon_i(\frac{dp}{p(i)} - \frac{dw_j}{w_j}) \tag{37}$$

This expression indicates that any input for which the relative wage increases less (more) than the relative cost of the tasks will experience an increase (decrease) in demand in task i. With 3 inputs, we can write the change in demand as follows:

$$\begin{aligned} d\mathcal{L}_j(i) &= \varepsilon_i(\frac{p(i)^{\varepsilon_i}(\delta_1(i)^{1-\varepsilon_i}w_1^{-\varepsilon_i}dw_1 + \delta_2(i)^{1-\varepsilon_i}w_2^{-\varepsilon_i}dw_2 + \delta_3(i)^{1-\varepsilon_i}w_3^{-\varepsilon_i}dw_3)}{p(i)} - \frac{dw_j}{w_j}) \\ &= \varepsilon_i(\frac{\delta_1(i)^{1-\varepsilon_i}w_1^{-\varepsilon_i}dw_1 + \delta_2(i)^{1-\varepsilon_i}w_2^{-\varepsilon_i}dw_2 + \delta_3(i)^{1-\varepsilon_i}w_3^{-\varepsilon_i}dw_3}{p(i)^{1-\varepsilon_i}} - \frac{dw_j}{w_j}) \\ d\mathcal{L}_j(i) &= \varepsilon_i(\frac{\delta_1(i)^{1-\varepsilon_i}w_1^{-\varepsilon_i}dw_1 + \delta_2(i)^{1-\varepsilon_i}w_2^{-\varepsilon_i}dw_2 + \delta_3(i)^{1-\varepsilon_i}w_3^{-\varepsilon_i}dw_3}{(\delta_1(i)w_1)^{1-\varepsilon_i} + (\delta_2(i)w_2)^{1-\varepsilon_i} + (\delta_3(i)w_3)^{1-\varepsilon_i}} - \frac{dw_j}{w_j}) \end{aligned} \tag{38}$$

M.1.1 When all inputs experience a decrease in wage

Let $\frac{dw_1}{w_1} < \frac{dw_2}{w_2} < \frac{dw_3}{w_3}$ which we can express as $dw_1 = aw_1$, $dw_2 = abw_2$, $dw_3 = acw_3$ with $a < 1$, $b, c \in (0, 1)$, and $b > c$. Then, (38) becomes:

$$d\mathcal{L}_j(i) = \varepsilon_i(a \underbrace{\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}}{(\delta_1(i)w_1)^{1-\varepsilon_i} + (\delta_2(i)w_2)^{1-\varepsilon_i} + (\delta_3(i)w_3)^{1-\varepsilon_i}}}_{\theta \in (0,1)} - \frac{dw_j}{w_j})$$

Given that b and c are both less than 1, it follows that $0 < \theta < 1$.

The change in demand for the first input is then given by the following equation.

$$d\mathcal{L}_1(i) = \varepsilon_i(a\theta - a)$$

Since $a < 0$, $d\mathcal{L}_1(i) > 0$ if $\theta < 1$ which holds always. The change in demand for the second input is given by $d\mathcal{L}_2(i) = \varepsilon_i(a\theta - ab)$. The demand for this input increases or is unchanged if $\theta \leq b$. By writing theta in its long form, we obtain:

$$\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}}{(\delta_1(i)w_1)^{1-\varepsilon_i} + (\delta_2(i)w_2)^{1-\varepsilon_i} + (\delta_3(i)w_3)^{1-\varepsilon_i}} \leq b$$

$$\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}}{b(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_3(i)w_3)^{1-\varepsilon_i}} \leq 1$$

This inequality may or may not hold. As a result, the change in the demand for the second input is indeterminate. The demand for the last input decreases when $d\mathcal{L}_3(i) = \varepsilon_i(a\theta - ac) < 0$. This occurs when $\theta > c$. By writing theta in its long form, we get:

$$\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}}{(\delta_1(i)w_1)^{1-\varepsilon_i} + (\delta_2(i)w_2)^{1-\varepsilon_i} + (\delta_3(i)w_3)^{1-\varepsilon_i}} > c$$

$$\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i}}{c(\delta_1(i)w_1)^{1-\varepsilon_i} + c(\delta_2(i)w_2)^{1-\varepsilon_i}} > 1$$

This inequality always holds since $b, c \in (0,1)$ and $c < b$.

M.1.2 When all inputs experience an increase in wage

Let $\frac{dw_1}{w_1} < \frac{dw_2}{w_2} < \frac{dw_3}{w_3}$ which we can express as $dw_1 = aw_1,\ dw_2 = abw_2,\ dw_3 = acw_3$ with $a > 1$, $b, c > 1$, and $b < c$. Then, (38) becomes:

$$d\mathcal{L}_j(i) = \varepsilon_i(a \underbrace{\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}}{(\delta_1(i)w_1)^{1-\varepsilon_i} + (\delta_2(i)w_2)^{1-\varepsilon_i} + (\delta_3(i)w_3)^{1-\varepsilon_i}}}_{\theta>1} - \frac{dw_j}{w_j})$$

Given that b and c are both greater than 1, it follows that $\theta > 1$.

The change in demand for the first input is then given by $d\mathcal{L}_1(i) = \varepsilon_i(a\theta - a)$. Given that $a > 0$, $d\mathcal{L}_1(i) > 0$ when $\theta > 1$ which always holds. The change in demand for the second input is indeterminate. Indeed, The demand for this input increases or is unchanged if $\theta \geq b$ which we can express as:

$$\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}}{b(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_3(i)w_3)^{1-\varepsilon_i}} \geq 1$$

Given that $b, c > 1$ and $b < c$, this inequality may or may not hold. The demand for the last input decreases when $d\mathcal{L}_3(i) = \varepsilon_i(a\theta - ac) < 0$. This occurs when $\theta < c$. By writing theta in its long form, we get:

$$\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i}}{c(\delta_1(i)w_1)^{1-\varepsilon_i} + c(\delta_2(i)w_2)^{1-\varepsilon_i}} < 1$$

This inequality always holds since $b, c > 1$ and $b < c$.

M.1.3 When some inputs experience an increase in wage

Let's assume that $\frac{dw_1}{w_1} < \frac{dw_2}{w_2} < \frac{dw_3}{w_3}$ and assume that input one and two see a fall in wage, but the wage of input 3 increases. We can express the wage changes as follows $dw_1 = aw_1,\ dw_2 = abw_2,\ dw_3 = acw_3$ with $a < 0$, $b \in (0, 1)$, and $c < 0$. Then, (38) becomes:

$$d\mathcal{L}_j(i) = \varepsilon_i(a \underbrace{\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}}{(\delta_1(i)w_1)^{1-\varepsilon_i} + (\delta_2(i)w_2)^{1-\varepsilon_i} + (\delta_3(i)w_3)^{1-\varepsilon_i}}}_{\theta<1} - \frac{dw_j}{w_j})$$

Given that b and c are both less than 1, it follows that $\theta < 1$. Since $a < 0$, $d\mathcal{L}_1(i) > 0$ if $\theta < 1$ which holds always. The demand for the second input increases or is unchanged if $\theta \leq b$. By writing theta in its long form, we obtain:

$$\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}}{(\delta_1(i)w_1)^{1-\varepsilon_i} + (\delta_2(i)w_2)^{1-\varepsilon_i} + (\delta_3(i)w_3)^{1-\varepsilon_i}} \leq b$$

$$\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}}{b(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_3(i)w_3)^{1-\varepsilon_i}} \leq 1$$

This inequality may or may not hold. The demand for the last input decreases when $\theta > c$. By writing theta in its long form, we get:

$$\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}}{(\delta_1(i)w_1)^{1-\varepsilon_i} + (\delta_2(i)w_2)^{1-\varepsilon_i} + (\delta_3(i)w_3)^{1-\varepsilon_i}} > c$$

$$\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i}}{c(\delta_1(i)w_1)^{1-\varepsilon_i} + c(\delta_2(i)w_2)^{1-\varepsilon_i}} < 1$$

This inequality always holds since $b \in (0,1)$ and $c < 0$.

Finally, Let's assume that $\frac{dw_1}{w_1} < \frac{dw_2}{w_2} < \frac{dw_3}{w_3}$ and assume that input one experiences a fall in wage, but the wage of input two and three increases. We can express the wage changes as follows $dw_1 = aw_1,\ dw_2 = abw_2,\ dw_3 = acw_3$ with $a < 0$, $b, c < 0$, and $b < c$. Then, (38) becomes:

$$d\mathcal{L}_j(i) = \varepsilon_i(a \underbrace{\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}}{(\delta_1(i)w_1)^{1-\varepsilon_i} + (\delta_2(i)w_2)^{1-\varepsilon_i} + (\delta_3(i)w_3)^{1-\varepsilon_i}}}_{\theta<1} - \frac{dw_j}{w_j})$$

Given that b and c are both less than 1, it follows that $\theta < 1$. Since $a < 0$, $d\mathcal{L}_1(i) > 0$ if $\theta < 1$ which holds always. The demand for the second input increases or is unchanged if $\theta \leq b$. By writing theta in its long form, we obtain:

$$\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}}{(\delta_1(i)w_1)^{1-\varepsilon_i} + (\delta_2(i)w_2)^{1-\varepsilon_i} + (\delta_3(i)w_3)^{1-\varepsilon_i}} \leq b$$

$$\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}}{b(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_3(i)w_3)^{1-\varepsilon_i}} \geq 1$$

This inequality may or may not hold. The demand for the last input decreases when $\theta > c$. By writing theta in its long form, we get:

$$\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}}{(\delta_1(i)w_1)^{1-\varepsilon_i} + (\delta_2(i)w_2)^{1-\varepsilon_i} + (\delta_3(i)w_3)^{1-\varepsilon_i}} > c$$

$$\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i}}{c(\delta_1(i)w_1)^{1-\varepsilon_i} + c(\delta_2(i)w_2)^{1-\varepsilon_i}} < 1$$

This inequality always holds since the left hand side is less than one when $b, c < 0$ and $b < c$. ■

M.2 Proposition 2

PROPOSITION 2 : *Suppose that tasks are more complementary than inputs within tasks such that $\sigma \geq 0$, $\sigma < \varepsilon_i \ \forall i$, and $\varepsilon_i > 0 \ \forall i$. In any task using inputs that all become cheaper, the demand will increase for the input that experiences the largest percentage decrease in wage. In tasks using inputs that all become more expensive, the demand for the input with the largest percentage increase in wage will decrease. In tasks using some inputs that become more expensive and some that become cheaper, the demand will increase for the input that experiences the largest percentage decrease in wage and decrease for the input with the largest percentage increase in wage. The change in demand is indeterminate for other inputs in those tasks.*

With 3 inputs, we can express Equation (8) as follows:

$$d\mathcal{L}_j(i) = (\varepsilon_i - \sigma)\left(\frac{\delta_1(i)^{1-\varepsilon_i} w_1^{-\varepsilon_i} dw_1 + \delta_2(i)^{1-\varepsilon_i} w_2^{-\varepsilon_i} dw_2 + \delta_3(i)^{1-\varepsilon_i} w_3^{-\varepsilon_i} dw_3}{(\delta_1(i)w_1)^{1-\varepsilon_i} + (\delta_2(i)w_2)^{1-\varepsilon_i} + (\delta_3(i)w_3)^{1-\varepsilon_i}}\right) - \varepsilon_i \frac{dw_j}{w_j} \tag{39}$$

M.2.1 When all inputs experience a decrease in wage

Let $\frac{dw_1}{w_1} < \frac{dw_2}{w_2} < \frac{dw_3}{w_3}$ which we can express as $dw_1 = aw_1$, $dw_2 = abw_2$, $dw_3 = acw_3$ with $a < 1$, $b, c \in (0, 1)$, and $b > c$. Then, (39) becomes:

$$d\mathcal{L}_j(i) = (\varepsilon_i - \sigma)(a\underbrace{\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}}{(\delta_1(i)w_1)^{1-\varepsilon_i} + (\delta_2(i)w_2)^{1-\varepsilon_i} + (\delta_3(i)w_3)^{1-\varepsilon_i}}}_{\theta\in(0,1)}) - \varepsilon_i\frac{dw_j}{w_j}$$

Given that b and c are both less than 1, it follows that $0 < \theta < 1$.

The change in demand for the first input is then given by the following equation.

$$d\mathcal{L}_1(i) = (\varepsilon_i - \sigma)(a\theta) - a\varepsilon_i$$

Since $a < 0$, $d\mathcal{L}_1(i) > 0$ if $\theta < \varepsilon_i/(\varepsilon_i - \sigma)$ which holds always since $\varepsilon_i/(\varepsilon_i - \sigma) > 1$. The change in demand for the second input is given by $d\mathcal{L}_2(i) = (\varepsilon_i - \sigma)(a\theta) - ab\varepsilon_i$. The demand for this input increases or is unchanged if $\theta \leq b\varepsilon_i/(\varepsilon_i - \sigma)$. By writing theta in its long form, we obtain:

$$\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}}{b(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i} + b(\delta_3(i)w_3)^{1-\varepsilon_i}} \leq \frac{\varepsilon_i}{(\varepsilon_i - \sigma)}$$

This inequality may or may not hold. As a result, the change in the demand for the second input is indeterminate. The demand for the last input decreases when $d\mathcal{L}_3(i) = (\varepsilon_i - \sigma)(a\theta) - ac\varepsilon_i < 0$. This occurs when $\theta > c\frac{\varepsilon_i}{(\varepsilon_i - \sigma)}$. By writing theta in its long form, we get:

$$\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}}{c(\delta_1(i)w_1)^{1-\varepsilon_i} + c(\delta_2(i)w_2)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}} > \frac{\varepsilon_i}{(\varepsilon_i - \sigma)}$$

This inequality holds when $\sigma = 0$ since $b, c \in (0,1)$ and $c < b$. However, it may not hold when $\sigma > 0$ since both sides are greater than one.

M.2.2 When all inputs experience an increase in wage

Let $\frac{dw_1}{w_1} < \frac{dw_2}{w_2} < \frac{dw_3}{w_3}$ which we can express as $dw_1 = aw_1$, $dw_2 = abw_2$, $dw_3 = acw_3$ with $a > 1$, $b, c > 1$, and $b < c$. Then, (39) becomes:

$$d\mathcal{L}_j(i) = (\varepsilon_i - \sigma)(a \underbrace{\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}}{(\delta_1(i)w_1)^{1-\varepsilon_i} + (\delta_2(i)w_2)^{1-\varepsilon_i} + (\delta_3(i)w_3)^{1-\varepsilon_i}}}_{\theta > 1}) - \varepsilon_i \frac{dw_j}{w_j}$$

Given that b and c are both greater than 1, it follows that $\theta > 1$.

The change in demand for the first input is then given by $d\mathcal{L}_1(i) = (\varepsilon_i - \sigma)(a\theta) - a\varepsilon_i$. Given that $a > 0$, $d\mathcal{L}_1(i) > 0$ when $\theta > \frac{\varepsilon_i}{(\varepsilon_i - \sigma)}$ which may or may not hold since both sides are greater than one.

The change in demand for the second input is indeterminate. Indeed, The demand for this input increases or is unchanged if $\theta \geq b$ which we can express as:

$$\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}}{b(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i} + b(\delta_3(i)w_3)^{1-\varepsilon_i}} \geq \frac{\varepsilon_i}{(\varepsilon_i - \sigma)}$$

Given that $b, c > 1$ and $b < c$, this inequality may or may not hold. The demand for the last input decreases when $d\mathcal{L}_3(i) = (\varepsilon_i - \sigma)(a\theta) - ac\varepsilon_i < 0$. This occurs when $\theta < c\frac{\varepsilon_i}{(\varepsilon_i - \sigma)}$. By writing theta in its long form, we get:

$$\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}}{c(\delta_1(i)w_1)^{1-\varepsilon_i} + c(\delta_2(i)w_2)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}} < \frac{\varepsilon_i}{(\varepsilon_i - \sigma)}$$

This inequality always holds since the left hand side is less than one when $b, c > 1$ and $b < c$ and the right hand side is greater than one.

M.2.3 When some inputs experience an increase in wage

Let's assume that $\frac{dw_1}{w_1} < \frac{dw_2}{w_2} < \frac{dw_3}{w_3}$ and assume that input one and two see a fall in wage, but the wage of input 3 increases. We can express the wage changes as follows $dw_1 = aw_1,\ dw_2 = abw_2,\ dw_3 = acw_3$ with $a < 0$, $b \in (0, 1)$, and $c < 0$. Then, (39) becomes:

$$d\mathcal{L}_j(i) = (\varepsilon_i - \sigma)(a\underbrace{\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}}{(\delta_1(i)w_1)^{1-\varepsilon_i} + (\delta_2(i)w_2)^{1-\varepsilon_i} + (\delta_3(i)w_3)^{1-\varepsilon_i}}}_{\theta<1}) - \frac{dw_j}{w_j}\varepsilon_i$$

Given that b and c are both less than 1, it follows that $\theta < 1$. Since $a < 0$, $d\mathcal{L}_1(i) > 0$ if $\theta < \frac{\varepsilon_i}{(\varepsilon_i - \sigma)}$ which holds always. The demand for the second input increases or is unchanged if $\theta \leq b\frac{\varepsilon_i}{(\varepsilon_i - \sigma)}$. By writing theta in its long form, we obtain:

$$\frac{(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i} + c(\delta_3(i)w_3)^{1-\varepsilon_i}}{b(\delta_1(i)w_1)^{1-\varepsilon_i} + b(\delta_2(i)w_2)^{1-\varepsilon_i} + b(\delta_3(i)w_3)^{1-\varepsilon_i}} \leq \frac{\varepsilon_i}{(\varepsilon_i - \sigma)}$$

This inequality may or may not hold. The demand for the last input decreases when $\theta > c\frac{\varepsilon_i}{(\varepsilon_i - \sigma)}$. By writing theta in its long form, we get:

$$\frac{(\delta_1(i)w_1)^{1-\varepsilon_i}+b(\delta_2(i)w_2)^{1-\varepsilon_i}+c(\delta_3(i)w_3)^{1-\varepsilon_i}}{c(\delta_1(i)w_1)^{1-\varepsilon_i}+c(\delta_2(i)w_2)^{1-\varepsilon_i}+c(\delta_3(i)w_3)^{1-\varepsilon_i}}<\frac{\varepsilon_i}{(\varepsilon_i-\sigma)}$$

This inequality always holds since the left had side is less than one when $b \in (0,1)$ and $c < 0$, while the right hand side is larger than one.

Finally, Let's assume that $\frac{dw_1}{w_1} < \frac{dw_2}{w_2} < \frac{dw_3}{w_3}$ and assume that input one experiences a fall in wage, but the wage of input two and three increases. We can express the wage changes as follows $dw_1 = aw_1,\ dw_2 = abw_2,\ dw_3 = acw_3$ with $a < 0$, $b, c < 0$, and $b < c$. Then, (39) becomes:

$$d\mathcal{L}_j(i)=(\varepsilon_i-\sigma)(a\underbrace{\frac{(\delta_1(i)w_1)^{1-\varepsilon_i}+b(\delta_2(i)w_2)^{1-\varepsilon_i}+c(\delta_3(i)w_3)^{1-\varepsilon_i}}{(\delta_1(i)w_1)^{1-\varepsilon_i}+(\delta_2(i)w_2)^{1-\varepsilon_i}+(\delta_3(i)w_3)^{1-\varepsilon_i}}}_{\theta<1})-\varepsilon_i\frac{dw_j}{w_j}$$

Given that b and c are both less than 1, it follows that $\theta < 1$. Since $a < 0$, $d\mathcal{L}_1(i) > 0$ if $\theta < \frac{\varepsilon_i}{(\varepsilon_i-\sigma)}$ which holds always. The demand for the second input increases or is unchanged if $\theta \leq b\frac{\varepsilon_i}{(\varepsilon_i-\sigma)}$. By writing theta in its long form, we obtain:

$$\frac{(\delta_1(i)w_1)^{1-\varepsilon_i}+b(\delta_2(i)w_2)^{1-\varepsilon_i}+c(\delta_3(i)w_3)^{1-\varepsilon_i}}{b(\delta_1(i)w_1)^{1-\varepsilon_i}+b(\delta_2(i)w_2)^{1-\varepsilon_i}+b(\delta_3(i)w_3)^{1-\varepsilon_i}}\geq\frac{\varepsilon_i}{(\varepsilon_i-\sigma)}$$

This inequality may or may not hold. The demand for the last input decreases when $\theta > c\frac{\varepsilon_i}{(\varepsilon_i-\sigma)}$. By writing theta in its long form, we get:

$$\frac{(\delta_1(i)w_1)^{1-\varepsilon_i}+b(\delta_2(i)w_2)^{1-\varepsilon_i}+c(\delta_3(i)w_3)^{1-\varepsilon_i}}{c(\delta_1(i)w_1)^{1-\varepsilon_i}+c(\delta_2(i)w_2)^{1-\varepsilon_i}+c(\delta_3(i)w_3)^{1-\varepsilon_i}}<\frac{\varepsilon_i}{(\varepsilon_i-\sigma)}$$

This inequality always holds since the left hand side is less than one when $b, c < 0$ and $b < c$. ■

N Estimates of elasticities of substitution

To get estimates for the elasticities of substitution, we need to make a series of simplifying assumptions about the model. First, let's assume that all tasks in firms in the average industry combine only regular workers and contract workers. Moreover, let's assume that all tasks are identical. In such case, the change in log-demand for input j is as follows. Given that tasks are identical and that there is a continuum of tasks on the interval 0-1, this is also the change in log-demand for that input at the firm level.

$$d\mathcal{L}_j = (\varepsilon^{lab} - \sigma)(\frac{dp}{p}) - \varepsilon^{lab}\frac{dw_j}{w_j}.$$

In the equation, ε^{lab} is the elasticity of substitution between labor inputs. The change in log-demand, dp/p and dw_j/w_j are the change in demand, price, and wages expressed in percentage. Let's rewrite the equation as follows:

$$\Delta\%x_j = (\varepsilon^{lab} - \sigma)(\Delta\%p) - \varepsilon^{lab}\Delta\%w_j,$$

where $\Delta\%x_j$ is the percentage change in demand for input j. $\Delta\%p$ and $\Delta\%w_j$ are the percentage change in the price of tasks and in the wage of input j. Taking the difference between the two inputs yields:

$$\frac{\Delta\%x_c - \Delta\%x_r}{(\Delta\%w_r - \Delta\%w_c)} = \varepsilon^{lab}.$$

To get a value, I use estimates from the change in number of employees working during a typical workday for firms in the first compensation group

(Table H.5, Column(2)). The average increase in the real minimum wage is 3.1%. If we assume that the wage of regular workers increases by that percentage and the wage of contract workers increases by half of that percentage we have $\varepsilon^{lab} = \frac{0.98\%+0.93\%}{(3.1\%-1.55)} = 1.24$. The elasticity gets larger if we assume that the wage of regular workers increases by less than 3.1% or if we assume that the effect on the wage of contract workers is more than half of the effect for regular workers.

For firms in industries more intensive in routine tasks (by one SD), let's assume that the output is produced by combining n identical labor tasks described above. The remaining $1-n$ tasks combine regular workers and capital. In these firms, the change in demand for regular workers, contract workers, and capital at the firm level are:

$$\Delta\%x_r = n[(\varepsilon^{lab} - \sigma)(\Delta\%p_{lab}) - \varepsilon^{lab}\Delta\%w_r] + (1-n)[(\varepsilon^{rk} - \sigma)(\Delta\%p_{rk}) - \varepsilon^{rk}\Delta\%w_r]$$
$$\Delta\%x_c = n[(\varepsilon^{lab} - \sigma)(\Delta\%p_{lab}) - \varepsilon^{lab}\Delta\%w_c]$$
$$\Delta\%x_k = (1-n)[(\varepsilon^{rk} - \sigma)(\Delta\%p_{rk}) - \varepsilon^{rk}\Delta\%w_k]$$

Taking the difference between the three inputs we get:

$$\Delta\%x_r - \Delta\%x_c - \Delta\%x_k = n\varepsilon^{lab}[\Delta\%w_c - \Delta\%w_r] + (1-n)\varepsilon^{rk}[\Delta\%w_k - \Delta\%w_r]$$

Then, plugging in the equation for the elasticity between labor inputs obtained above, we obtain:

$$\varepsilon^{rk} = \frac{\Delta\%x_r - \Delta\%x_c - \Delta\%x_k - n[\Delta\%x_c - \Delta\%x_r]}{(1-n)[\Delta\%w_k - \Delta\%w_r]}$$

To get a value of the elasticity, I use estimates from the same specification as before for the change in demand for regular workers. Assuming that 10% of tasks are labor tasks, that there is no change in employment of contract workers, that the wage of regular workers increases by 3.1%, and that the price of capital falls by 0.1% (Karabarbounis and Neiman (2014)), we have $\varepsilon^{rk} = \frac{-0.5\% - 6.5\% + 0.1[0.5\%]}{0.9[-0.1\% - 3.1\%]} = 2.4$. The elasticity gets larger if the proportion of labor tasks increases, if the number of contract workers increases, and when the wage of regular workers increases by less than 3.1%.

VI

Appendices for Chapter II: Absenteeism, Productivity, and Relational Contracts Inside the Firm

O Distance and demographics

In our counterfactual analysis, we construct a binary variable equal to 1 whenever the managers in a pair have any demographic differences. More precisely, this variable equals 1 when managers are of different genders, or have a different level of education, or their age difference is above median, or their experience difference in managing their current line is above the median.

We regress this variable on physical distance and separately on a dummy for whether managers are on a different floor to see if similar managers are clustered together by the firm perhaps to promote cooperation.

Table O.1: Relationship between demographic difference and location in the factory

	Demographic distance		
	(1) OLS	(2) Probit	(3) Logit
Physical distance	0.0000	0.0000	0.0000
	(0.0036)	(0.0237)	(0.0500)
Pairs	204	204	204
Diff. floor	0.0280	0.2258	0.4737
	(0.0206)	(0.1526)	(0.3159)
Pairs	864	864	864

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress the indicator variable for demographic differences on physical distance for lines on the same floor and on a dummy variable for whether the pair is on a different floor separately. In parentheses, we report robust standard errors.

Table O.2: Correlations between physical distance and demographic variables

	Distance	**Gender difference**	**Education difference**	**Age difference**	**Exp. on this line difference**
Distance	1				
Gender difference	0.005	1			
Education difference	-0.081	0.009	1		
Age difference	0.122	0.010	0.073	1	
Exp. on this line difference	-0.063	0.074	-0.035	-0.049	1

Note: We present the correlations between physical distance and the demographic distance variables for the 204 pairs of managers on a same floor.

As is evident, on a given floor, managers that are further away from one another are not more likely to be demographically dissimilar than managers that are close by. Though the point estimates are positive, managers on different floors are not statistically more likely to be dissimilar than managers on a same floor either. This suggests that the placement of managers by the firm does not appear to be related to how similar the managers are. Furthermore, none of these demographic variables are highly correlated between one another or with physical distance as we can see from Table O.2.

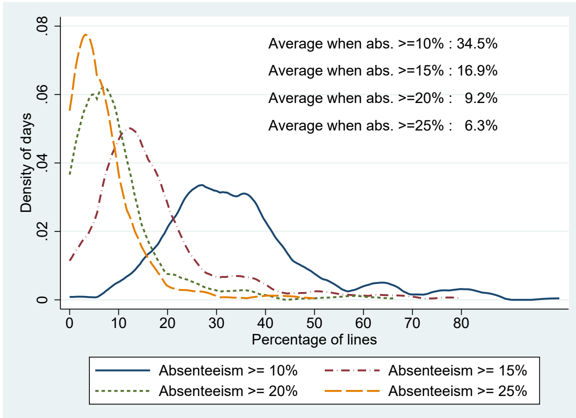
Table O.3: Sample composition of managers

Demographics	**Percent**
Male	87.67
Kannada	75.34
Hindu	97.26
General caste	43.84
Passed 10th grade	41.10
From Karnataka state	71.23

Note: For each demographic variable we show the most common category across managers in the sample. Kannada is the native language and Karnataka state indicates being born in Karnataka but outside of the Bengaluru metropolitan area.

P Absenteeism shocks are uncorrelated and frequent

Figure P.1: Frequency of large absenteeism shocks



Note: We calculate the percentage of lines with an absenteeism level of at least 10%, 15%, 20%, and 25% on a given day. We take the average number of lines which such shock across days and plot the distribution. We report the average number of lines with at least a 10%, 15%, 20%, and 25% absenteeism shock. For example, we find that 34.5% (9.2%) of lines have at least a 10% (20%) absenteeism shock on any given day.

Table P.1: Intracluster correlation of absenteeism across factories, within factories, and within floors

	Correlation of Absenteeism		
	Within Date	Within Unit and Date	Within floor and Date
Correlation	0.068	0.143	0.145
(SE)	(0.007)	(0.009)	(0.009)

Note: Standard errors are in parenthesis. In column 1, we show the within-day correlation of line-level absenteeism across all lines averaged across days. Column 2 shows the correlation of within-day line-level absenteeism within units averaged across days. Finally, column 3 shows the within-day correlation of line-level absenteeism within factory floors averaged across days.

Q Robustness to using all dyads

Table Q.1: Tests of model predictions on the extensive margin

	Any number of workers borrowed		
	(1)	(2)	(3)
$(\%Abs\, i - \%Abs\, j)/2$	568.7733	124.3410	120.7499
	(0.0241) **	(0.0446) **	(0.0431) **
	[0.0237] **	[0.0445] **	[0.0432] **
	{0.1166}	{0.1130}	{0.1081}
log(Maturity of relationship)	1.8444	4.4665	4.4677
	(0.0000) ***	(0.0000) ***	(0.0000) ***
	[0.0000] ***	[0.0000] ***	[0.0000] ***
	{0.0000} ***	{0.0000} ***	{0.0000} ***
log(Distance)	0.4655	0.7898	0.7898
	(0.0000) ***	(0.0222) **	(0.0221) **
	[0.0000] ***	[0.0308] **	[0.0322] **
	{0.0000} ***	{0.1026}	{0.1033}
	Identity-based distance		
Different gender	0.4685	0.4726	0.4724
	(0.0060) ***	(0.0027) ***	(0.0027) ***
	[0.0066] ***	[0.0026] ***	[0.0025] ***
	{0.0980}*	{0.0979}*	{0.0976}*
Different education	0.5920	0.7351	0.7352
	(0.0000) ***	(0.0044) ***	(0.0044) ***
	[0.0001] ***	[0.0111] **	[0.0125] **
	{0.0000} ***	{0.0072} ***	{0.0073} ***
log(Difference in age of managers)	0.9712	0.9554	0.9555
	(0.1248)	(0.0176) **	(0.0175) **
	[0.1447]	[0.0234] **	[0.0237] **
	{0.1885}	{0.0397} **	{0.0405} **
log(Diff. in exp. on the line)	0.8493	0.7934	0.7934
	(0.0882)*	(0.0102) **	(0.0102) **
	[0.0885]*	[0.0104] **	[0.0103] **
	{0.0937}*	{0.0263} **	{0.0261} **
Observations	28813	28813	28813
Mean of Y	.188	.188	.188
SD	.176	.176	.176

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress a dummy for whether i borrows any number worker from j at the daily manager-pair level on the average difference in absenteeism in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers are of different gender, a dummy for whether they have a different level of education, on their log age difference, and on their log difference in their experience managing their respective lines. We include dyads on a same floor for which the average difference in absenteeism in the pair is greater or equal to 0. In parentheses, we report *p-values* for standard errors clustered at the pair level. In square brackets, we report *p-values* for 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report *p-values* for 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each managers as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 has the same fixed effects as column 2, and we also control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

Table Q.2: Tests of model predictions keeping all dyads

	Number of workers borrowed		
	(1)	(2)	(3)
$(\%Abs\, i - \%Abs\, j)/2$	5.7479	4.8996	4.5722
	(2.1266) $***$	(2.1049) $**$	(2.0348) $**$
	[2.1254] $***$	[2.1064] $**$	[2.0381] $**$
	{2.6984} $**$	{2.3987} $**$	{2.3589}$*$
log(Maturity of relationship)	0.4063	1.2654	1.2694
	(0.1093) $***$	(0.0789) $***$	(0.0787) $***$
	[0.1104] $***$	[0.0787] $***$	[0.0785] $***$
	{0.1163} $***$	{0.0845} $***$	{0.0843} $***$
log(Distance)	−0.7789	−0.2664	−0.2643
	(0.1137) $***$	(0.0785) $***$	(0.0784) $***$
	[0.1151] $***$	[0.0795] $***$	[0.0795] $***$
	{0.1279} $***$	{0.0976} $***$	{0.0976} $***$
	Identity-based distance		
Different gender	−0.7767	−0.8749	−0.8758
	(0.3371) $**$	(0.3315) $***$	(0.3314) $***$
	[0.3341] $**$	[0.3307] $***$	[0.3308] $***$
	{0.2465} $***$	{0.2909} $***$	{0.2910} $***$
Different education	−0.4178	−0.1219	−0.1211
	(0.1371) $***$	(0.0877)	(0.0875)
	[0.1374] $***$	[0.0870]	[0.0869]
	{0.1431} $***$	{0.1017}	{0.1020}
log(Difference in age of managers)	−0.0131	−0.0271	−0.0271
	(0.0172)	(0.0136) $**$	(0.0136) $**$
	[0.0172]	[0.0136] $**$	[0.0136] $**$
	{0.0176}	{0.0145}$*$	{0.0146}$*$
log(Diff. in exp. on the line)	−0.0637	−0.1474	−0.1469
	(0.0944)	(0.0655) $**$	(0.0655) $**$
	[0.0937]	[0.0649] $**$	[0.0649] $**$
	{0.0783}	{0.0651} $**$	{0.0650} $**$
Observations	47847	47847	47847
Mean of Y	.24	.24	.24
SD	.928	.928	.928
Effect when X1= 1%	5.92 %	5.02 %	4.68 %
Effect when X1= 5%	33.29 %	27.76 %	25.69 %

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress the daily number of workers borrowed at the manager-pair level on the average difference in absenteeism in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers are of different gender, a dummy for whether they have a different level of education, on their log age difference, and on their log difference in their experience managing their respective lines. All dyads that are on a same floor are included. In parentheses, we report standard errors clustered at the pair level. In square brackets, we report 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each managers as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 has the same fixed effects as column 2, and we also control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

In the main results section of the essay, we keep only dyads where $(\frac{\%Abs\,i - \%Abs\,j}{2}) \geq 0$. In table Q.2, we keep all dyads and the main regressor is equal to $(\frac{\%Abs\,i - \%Abs\,j}{2})$ whenever $(\frac{\%Abs\,i - \%Abs\,j}{2}) \geq 0$ and is equal to 0 otherwise. In order not to drop dyads, we control for a dummy variable equal to 1 when $(\frac{\%Abs\,i - \%Abs\,j}{2}) < 0$ and 0 otherwise. The results are very similar to what we found before.

Table Q.3: Tests of model predictions controlling for whether managers in a dyad work on the same style of garment

	Number of workers borrowed		
	(1)	(2)	(3)
$(\%Abs\ i - \%Abs\ j)/2$	5.9146	5.3276	4.9737
	(2.0679) ***	(1.7867) ***	(1.6948) ***
	[2.0764] ***	[1.8015] ***	[1.7172] ***
	{2.5763} **	{2.0094} ***	{1.9408} **
log(Maturity of relationship)	0.3474	1.3107	1.3140
	(0.1186) ***	(0.0868) ***	(0.0864) ***
	[0.1201] ***	[0.0877] ***	[0.0872] ***
	{0.1357} **	{0.0929} ***	{0.0927} ***
log(Distance)	−0.8458	−0.2554	−0.2544
	(0.1181) ***	(0.0835) ***	(0.0832) ***
	[0.1194] ***	[0.0853] ***	[0.0850] ***
	{0.1281} ***	{0.0917} ***	{0.0914} ***
	Identity-based distance		
Different gender	−0.9614	−1.0094	−1.0118
	(0.2392) ***	(0.2099) ***	(0.2123) ***
	[0.2334] ***	[0.2060] ***	[0.2089] ***
	{0.3384} ***	{0.3559} ***	{0.3581} ***
Different education	−0.5029	−0.1836	−0.1838
	(0.1288) ***	(0.0915) **	(0.0913) **
	[0.1305] ***	[0.0923] **	[0.0923] **
	{0.1255} ***	{0.0816} **	{0.0812} **
log(Difference in age of managers)	−0.0272	−0.0474	−0.0476
	(0.0187)	(0.0157) ***	(0.0157) ***
	[0.0186]	[0.0156] ***	[0.0156] ***
	{0.0193}	{0.0162} ***	{0.0164} ***
log(Diff. in exp. on the line)	−0.1736	−0.2720	−0.2711
	(0.0977)*	(0.0790) ***	(0.0789) ***
	[0.0967]*	[0.0778] ***	[0.0776] ***
	{0.0787} **	{0.0806} ***	{0.0804} ***
Observations	27560	27560	27560
Mean of Y	.215	.215	.215
SD	.853	.853	.853
Effect when X1= 1%	6.09 %	5.47 %	5.10%
Effect when X1= 5%	34.41 %	30.52 %	28.23 %

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress the daily number of workers borrowed at the manager-pair level on the average difference in absenteeism in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers are of different gender, a dummy for whether they have a different level of education, on their log age difference, and on their log difference in their experience managing their respective lines. In all specifications, we include a dummy variable equal to one if the two managers in the dyad work on the same style of garment. All dyads that are on a same floor are included. In parentheses, we report standard errors clustered at the pair level. In square brackets, we report 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each managers as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 has the same fixed effects as column 2, and we also control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

R Quality

Here, we show that there is heterogeneity in trade behavior with regards to worker "quality." Instead of looking at the aggregate number of workers borrowed (as in the previous analysis), we separated workers by whether their efficiency is below or above the median. To group the workers into efficiency quartiles, we first net their daily efficiency of unit, line, garment style, and date fixed effects. Then, we compute the workers' average (residual) efficiency over the span of the data.

Table R.1: Lower efficiency workers

	Nb. Below Med. eff.		
	(1)	(2)	(3)
$(\%Abs\ i - \%Abs\ j)/2$	6.2394	5.7413	5.6716
	(1.3226) ∗∗∗	(1.3434) ∗∗∗	(1.3146) ∗∗∗
	[1.3050] ∗∗∗	[1.3269] ∗∗∗	[1.2967] ∗∗∗
	{1.6472} ∗∗∗	{1.5434} ∗∗∗	{1.5400} ∗∗∗
log(Maturity of relationship)	2.1077	1.6512	1.6343
	(0.5689) ∗∗∗	(0.4664) ∗∗∗	(0.4603) ∗∗∗
	[0.5790] ∗∗∗	[0.4657] ∗∗∗	[0.4595] ∗∗∗
	{0.6277} ∗∗∗	{0.4838} ∗∗∗	{0.4763} ∗∗∗
log(Maturity of relationship)^2	−0.2427	−0.0371	−0.0343
	(0.0844) ∗∗∗	(0.0674)	(0.0665)
	[0.0859] ∗∗∗	[0.0674]	[0.0665]
	{0.0959} ∗∗	{0.0709}	{0.0698}
log(Distance)	−0.6763	−0.0586	−0.0579
	(0.1437) ∗∗∗	(0.1315)	(0.1313)
	[0.1443] ∗∗∗	[0.1317]	[0.1316]
	{0.1578} ∗∗∗	{0.1490}	{0.1487}
	Identity-based distance		
Different gender	−0.8434	−0.8697	−0.8685
	(0.4078) ∗∗	(0.3682) ∗∗	(0.3695) ∗∗
	[0.4074] ∗∗	[0.3707] ∗∗	[0.3722] ∗∗
	{0.3883} ∗∗	{0.4035} ∗∗	{0.4026} ∗∗
Different education	−0.3788	−0.0709	−0.0703
	(0.1732) ∗∗	(0.1417)	(0.1417)
	[0.1723] ∗∗	[0.1406]	[0.1407]
	{0.1803} ∗∗	{0.1559}	{0.1558}
log(Difference in age of managers)	−0.0168	−0.0285	−0.0283
	(0.0240)	(0.0218)	(0.0217)
	[0.0242]	[0.0218]	[0.0218]
	{0.0255}	{0.0219}	{0.0219}
log(Diff. in exp. on the line)	−0.2001	−0.2137	−0.2142
	(0.1228)	(0.1113)∗	(0.1112)∗
	[0.1210]∗	[0.1090] ∗∗	[0.1088] ∗∗
	{0.1237}	{0.1193}∗	{0.1194}∗
Observations	29091	29091	29091
Mean of Y	.098	.098	.098
SD	.462	.462	.462
Effect when X1= 1%	6.44 %	5.91 %	5.84 %
Effect when X1= 5%	36.61 %	33.25 %	32.79 %

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress the daily number of below-median efficiency workers borrowed at the manager-pair level on the average difference in absenteeism of these workers in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers are of different gender, a dummy for whether they have a different level of education, on their log age difference, and on their log difference in their experience managing their respective lines. We include dyads on a same floor for which the average difference in absenteeism of below-median efficiency workers in the pair is greater or equal to 0. In parentheses, we report standard errors clustered at the pair level. In square brackets, we report 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each managers as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 has the same fixed effects as column 2, and we also control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

In Table R.1, we regress the number of lower efficiency workers borrowed on the difference in absenteeism of lower efficiency workers in the dyad that day and the same controls as in our main specifications.[163] We show the corresponding results for higher efficiency workers in Table R.2.[164]

[163] We add $\ln(\text{Maturity})^2$ to better see the nuance in the effect of maturity between high and low quality workers.

[164] In Tables R.3 and R.4, we present the same regressions where we use overall differences in absenteeism on the RHS as in Table 12 instead of the difference in absenteeism of low (high) efficiency workers as in Table R.1 (R.2).

Table R.2: Higher efficiency workers

	Nb. above Med. eff.		
	(1)	(2)	(3)
$(\%Abs\ i - \%Abs\ j)/2$	2.8437	2.9186	2.7279
	(1.5386)*	(1.2620)**	(1.1979)**
	[1.5450]*	[1.2713]**	[1.2124]**
	{1.7882}	{1.3863}**	{1.3062}**
log(Maturity of relationship)	3.0446	2.6004	2.6033
	(0.6574)***	(0.6149)***	(0.6101)***
	[0.6740]***	[0.6274]***	[0.6227]***
	{0.7871}***	{0.6658}***	{0.6648}***
log(Maturity of relationship)^2	−0.3805	−0.1954	−0.1950
	(0.0955)***	(0.0869)**	(0.0858)**
	[0.0972]***	[0.0882]**	[0.0871]**
	{0.1160}***	{0.0975}**	{0.0970}**
log(Distance)	−1.1565	−0.5794	−0.5748
	(0.1349)***	(0.0993)***	(0.0983)***
	[0.1347]***	[0.0999]***	[0.0988]***
	{0.1470}***	{0.1018}***	{0.1003}***
	Identity-based distance		
Different gender	−1.2549	−1.2042	−1.2130
	(0.2375)***	(0.2397)***	(0.2379)***
	[0.2322]***	[0.2370]***	[0.2347]***
	{0.1570}***	{0.1781}***	{0.1820}***
Different education	−0.5378	−0.2830	−0.2833
	(0.1406)***	(0.0924)***	(0.0927)***
	[0.1411]***	[0.0923]***	[0.0927]***
	{0.1555}***	{0.1062}***	{0.1066}***
log(Difference in age of managers)	−0.0695	−0.0792	−0.0793
	(0.0244)***	(0.0214)***	(0.0215)***
	[0.0244]***	[0.0216]***	[0.0217]***
	{0.0252}***	{0.0224}***	{0.0226}***
log(Diff. in exp. on the line)	−0.3090	−0.3545	−0.3533
	(0.1057)***	(0.0916)***	(0.0918)***
	[0.1044]***	[0.0909]***	[0.0912]***
	{0.0986}***	{0.0828}***	{0.0838}***
Observations	28492	28492	28492
Mean of Y	.113	.113	.113
SD	.498	.498	.498
Effect when X1= 1%	2.88 %	2.96 %	2.77 %
Effect when X1= 5%	15.28 %	15.71 %	14.61 %

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress the daily number of above-median efficiency workers borrowed at the manager-pair level on the average difference in absenteeism of these workers in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers are of different gender, a dummy for whether they have a different level of education, on their log age difference, and on their log difference in their experience managing their respective lines. We include dyads on a same floor for which the average difference in absenteeism of above-median efficiency workers in the pair is greater or equal to 0. In parentheses, we report standard errors clustered at the pair level. In square brackets, we report 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each managers as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 has the same fixed effects as column 2, and we also control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

We find that the difference in absenteeism of low efficiency workers, maturity, gender, and differences in experience have a similar significant effect as we found in the pooled regression of Table 12. However, other demographics as well as physical distance have no statistical impact on this number, though the point estimates remain negative. On the other hand, the difference in absenteeism in higher efficiency workers have a smaller effect on the number of high efficiency workers borrowed compared to the pooled regression, but the point estimates are all larger in magnitude for the rest of the coefficients. This latter feature suggests that physical distance and demographics differences between managers are more important when it comes to trading more valuable workers. In particular, the effect of maturity is always larger for high quality workers given the support of the data than it is for low quality workers indicating that trust is particularly important for better workers.

Tables R.3 and R.4 are analogous to Tables R.1 and R.2, however the absenteeism variable represents the difference in *total* absenteeism. That is, the difference in absenteeism of workers with efficiency below *and* above the median as in Table 12.

Table R.3: Lower efficiency workers

	Number of workers borrowed with efficiency below the median		
	(1)	(2)	(3)
$(\%Abs\, i - \%Abs\, j)/2$	6.3244	6.1064	5.8654
	(2.0744) $***$	(1.8705) $***$	(1.8048) $***$
	[2.0980] $***$	[1.8941] $***$	[1.8303] $***$
	{2.8343} $**$	{2.3975} $**$	{2.3951} $**$
log(Maturity of relationship)	0.3789	1.4180	1.4199
	(0.1248) $***$	(0.1229) $***$	(0.1226) $***$
	[0.1265] $***$	[0.1248] $***$	[0.1246] $***$
	{0.1392} $***$	{0.1404} $***$	{0.1404} $***$
log(Distance)	−0.6299	−0.0318	−0.0321
	(0.1338) $***$	(0.1210)	(0.1208)
	[0.1355] $***$	[0.1216]	[0.1215]
	{0.1483} $***$	{0.1337}	{0.1334}
	Identity-based distance		
Different gender	−0.8545	−0.9041	−0.9059
	(0.3953) $**$	(0.3614) $**$	(0.3633) $**$
	[0.3930] $**$	[0.3629] $**$	[0.3649] $**$
	{0.3995} $**$	{0.4202} $**$	{0.4221} $**$
Different education	−0.4365	−0.0464	−0.0464
	(0.1712) $**$	(0.1367)	(0.1368)
	[0.1716] $**$	[0.1367]	[0.1368]
	{0.1881} $**$	{0.1446}	{0.1446}
log(Difference in age of managers)	−0.0047	−0.0262	−0.0261
	(0.0223)	(0.0213)	(0.0212)
	[0.0220]	[0.0207]	[0.0207]
	{0.0212}	{0.0199}	{0.0200}
log(Diff. in exp. on the line)	−0.1618	−0.2629	−0.2633
	(0.1263)	(0.1124) $**$	(0.1123) $**$
	[0.1247]	[0.1111] $**$	[0.1110] $**$
	{0.1203}	{0.1025} $**$	{0.1025} $**$
Observations	27560	27560	27560
Mean of Y	.099	.099	.099
SD	.468	.468	.468
Effect when X1= 1%	6.53 %	6.3 %	6.04 %
Effect when X1= 5%	37.19 %	35.71 %	34.08 %

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress the daily number of below-median efficiency workers borrowed at the manager-pair level on the average difference in absenteeism of all workers in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers are of different gender, a dummy for whether they have a different level of education, on their log age difference, and on their log difference in their experience managing their respective lines. We include dyads on a same floor for which the average difference in absenteeism of all workers in the pair is greater or equal to 0. In parentheses, we report standard errors clustered at the pair level. In square brackets, we report 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each managers as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 has the same fixed effects as column 2, and we also control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

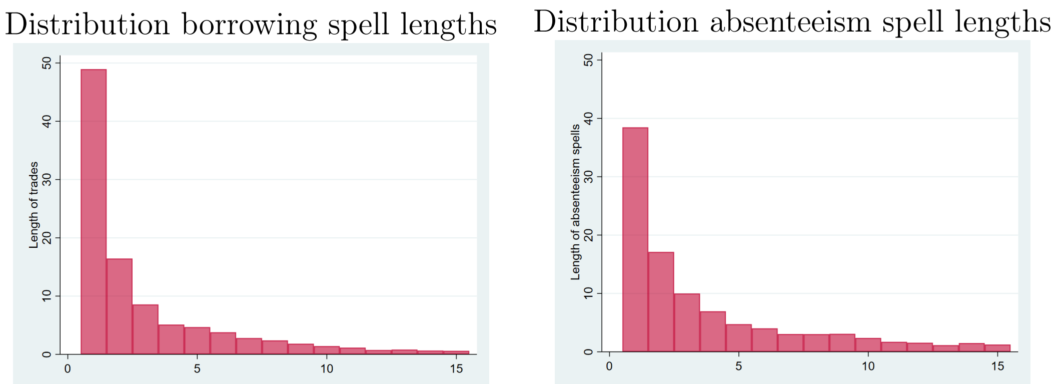
Table R.4: Higher efficiency workers

	Nb. above Med. eff.		
	(1)	(2)	(3)
$(\%Abs\, i - \%Abs\, j)/2$	5.1468	4.4450	3.9507
	(2.1755) **	(2.0689) **	(1.9814) **
	[2.1579] **	[2.0665] **	[1.9847] **
	{2.4515} **	{2.1238} **	{2.0116} **
log(Maturity of relationship)	2.7917	2.4619	2.4633
	(0.6430) ***	(0.6349) ***	(0.6271) ***
	[0.6650] ***	[0.6500] ***	[0.6425] ***
	{0.7922} ***	{0.6900} ***	{0.6874} ***
log(Maturity of relationship)^2	−0.3465	−0.1769	−0.1760
	(0.0926) ***	(0.0893) **	(0.0878) **
	[0.0949] ***	[0.0911]*	[0.0897] **
	{0.1162} ***	{0.1006}*	{0.0999}*
log(Distance)	−1.1661	−0.5901	−0.5879
	(0.1386) ***	(0.1031) ***	(0.1022) ***
	[0.1383] ***	[0.1038] ***	[0.1028] ***
	{0.1426} ***	{0.0934} ***	{0.0927} ***
	Identity-based distance		
Different gender	−1.2616	−1.2157	−1.2229
	(0.2068) ***	(0.2133) ***	(0.2116) ***
	[0.2016] ***	[0.2061] ***	[0.2047] ***
	{0.1522} ***	{0.1810} ***	{0.1851} ***
Different education	−0.5918	−0.3451	−0.3452
	(0.1417) ***	(0.0980) ***	(0.0978) ***
	[0.1440] ***	[0.0996] ***	[0.0997] ***
	{0.1363} ***	{0.0886} ***	{0.0885} ***
log(Difference in age of managers)	−0.0763	−0.0866	−0.0869
	(0.0263) ***	(0.0222) ***	(0.0224) ***
	[0.0261] ***	[0.0220] ***	[0.0222] ***
	{0.0300} **	{0.0244} ***	{0.0247} ***
log(Diff. in exp. on the line)	−0.2602	−0.3237	−0.3232
	(0.1019) **	(0.0922) ***	(0.0923) ***
	[0.1009] ***	[0.0905] ***	[0.0905] ***
	{0.1003} ***	{0.1008} ***	{0.1004} ***
Observations	27560	27560	27560
Mean of Y	.116	.116	.116
SD	.511	.511	.511
Effect when X1= 1%	5.28 %	4.55 %	4.03 %
Effect when X1= 5%	29.35 %	24.89 %	21.84 %

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress the daily number of above-median efficiency workers borrowed at the manager-pair level on the average difference in absenteeism of all workers in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers are of different gender, a dummy for whether they have a different level of education, on their log age difference, and on their log difference in their experience managing their respective lines. We include dyads on a same floor for which the average difference in absenteeism of all workers in the pair is greater or equal to 0. In parentheses, we report standard errors clustered at the pair level. In square brackets, we report 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each managers as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 has the same fixed effects as column 2, and we also control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

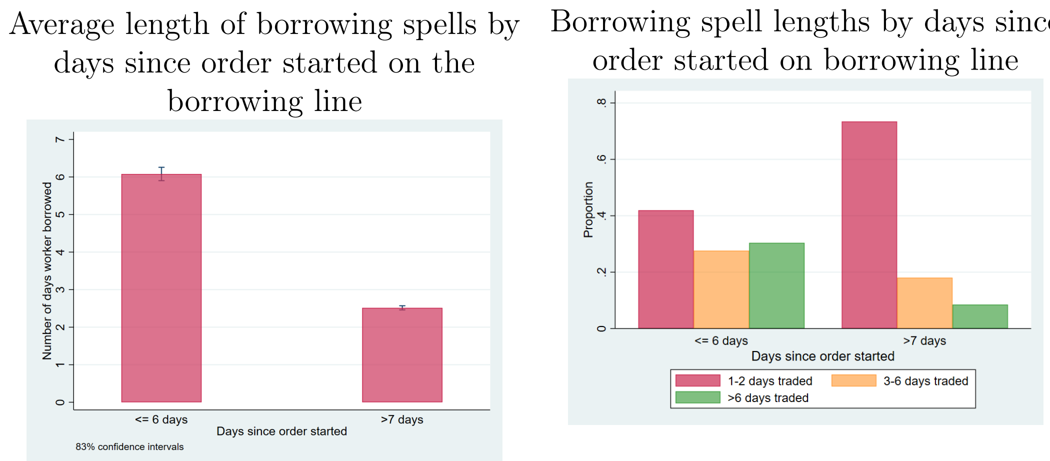
S Excluding Trades Likely to be Centrally Planned

Figure S.1: Distribution of trade and absenteeism spells



Note: We calculate the number of days workers spend on another line when traded to that line and plot the distribution across all trades in the left panel. As in the rest of the analysis, when a worker spends more than 15 consecutive work-days on another line, we assume that they have switched home-line and do not count these movements as trades. Work-days span from Monday to Saturday includive. In the right panel, we count the number of work-days for which workers are absent for every absenteeism spells and plot the distribution over the same range as in the left panel.

Figure S.2: Trade Spells

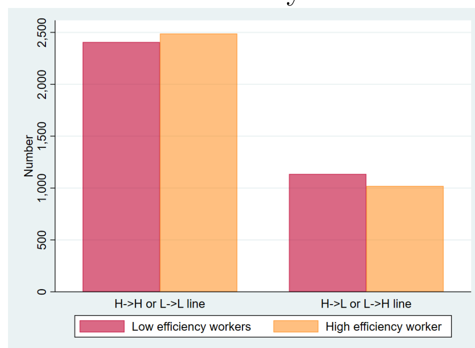


Note: We plot the average length of trade spells for workers borrowed depending on whether the borrowing line was in the first work-week of an order or not in the left panel. We plot 83.4% confidence intervals. 83.4% intervals that do not overlap indicate that 2 means are different at the 95% level when the samples are independent. In the right panel, we show the distribution of short, medium, and long trades to borrowing lines depending on whether the borrowing line was in the first work-week of an order or not.

Figure S.3: Number of high and low efficiency workers traded within each type of partnership

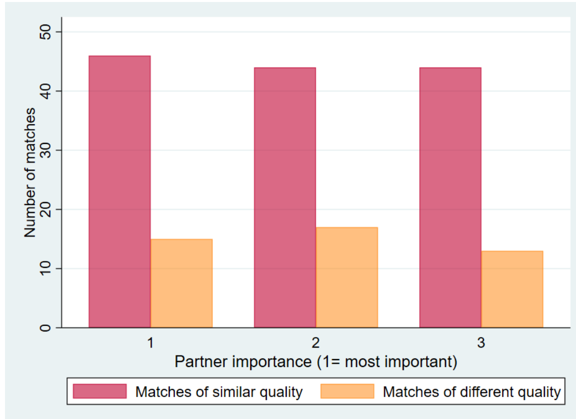
Excluding the first week of the borrower's order

Excluding trade spells lasting six or more days



Note: We first obtain manager and worker fixed effects from the same AKM specification used in Figure U.3 and then split the sample of managers at the median within unit and floor and split the workers at the median within unit. This ensures that there are high and low quality workers and managers on each floor. We count the number of high and low efficiency workers traded from high efficiency lines to high efficiency lines, from low efficiency lines to low efficiency lines, and from high (low) efficiency lines to low (high) efficiency line. We plot these numbers when excluding trades going to borrowing lines in the first week of an order in the left panel, and when excluding long trades (longer than 5 days) in the right panel.

Figure S.4: Number of main partnerships of similar and different quality level



Note: We obtain the same manager effects used in Figure S.3 and split again at the median within unit and floor such that there are high and low quality managers in each unit-floor. We look at every manager's first, second, and third most frequent partners and count how many matches are between managers of similar and different quality level. Managers are of similar efficiency levels if they both are high efficiency managers or both low efficiency mangers. They are different otherwise. Manager A can have manager B as her most important partner, but manager A may not be manager B's most important partner. Hence, for the first bar for example, we count the *number of managers* that have a first partner with similar level of efficiency. We *do not count the number of pairs* of managers that see one another as main partners and are similar in terms of efficiency.

Table S.1: Tests of model predictions when excluding long trades (6 days or more)

	Number of workers borrowed		
	(1)	(2)	(3)
$(\%Abs\ i - \%Abs\ j)/2$	6.0416	5.8510	5.7414
	(2.1840) * **	(1.9574) * **	(1.8823) * **
	[2.1636] * **	[1.9159] * **	[1.8456] * **
	{2.6263} * *	{2.4984} * *	{2.4032} * *
log(Maturity of relationship)	0.3176	1.1589	1.1599
	(0.0792) * **	(0.0897) * **	(0.0896) * **
	[0.0815] * **	[0.0890] * **	[0.0889] * **
	{0.0863} * **	{0.0999} * **	{0.0998} * **
log(Distance)	−0.7113	−0.2064	−0.2065
	(0.0951) * **	(0.0780) * **	(0.0779) * **
	[0.0981] * **	[0.0814] * *	[0.0813] * *
	{0.0957} * **	{0.0904} * *	{0.0902} * *
	Identity-based distance		
Different gender	−0.5926	−0.6421	−0.6433
	(0.1835) * **	(0.1729) * **	(0.1733) * **
	[0.1687] * **	[0.1560] * **	[0.1565] * **
	{0.3126}*	{0.3105} * *	{0.3123} * *
Different education	−0.3421	−0.0511	−0.0510
	(0.1092) * **	(0.0727)	(0.0726)
	[0.1129] * **	[0.0753]	[0.0753]
	{0.1165} * **	{0.0929}	{0.0927}
log(Difference in age of managers)	−0.0376	−0.0501	−0.0501
	(0.0193)*	(0.0159) * **	(0.0159) * **
	[0.0187] * *	[0.0153] * **	[0.0153] * **
	{0.0230}	{0.0178} * **	{0.0178} * **
log(Diff. in exp. on the line)	−0.0958	−0.1484	−0.1487
	(0.0820)	(0.0588) * *	(0.0588) * *
	[0.0813]	[0.0579] * *	[0.0579] * *
	{0.0643}	{0.0575} * **	{0.0574} * **
Observations	27560	27560	27560
Mean of Y	.098	.098	.098
SD	.447	.447	.447
Effect when X1= 1%	6.23 %	6.03 %	5.91 %
Effect when X1= 5%	35.27 %	33.98 %	33.25 %

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We exclude trades longer than five work-days. We regress the daily number of workers borrowed at the manager-pair level on the average difference in absenteeism in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers are of different gender, a dummy for whether they have a different level of education, on their log age difference, and on their log difference in their experience managing their respective lines. We include dyads on a same floor for which the average difference in absenteeism in the pair is greater or equal to 0. In parentheses, we report standard errors clustered at the pair level. In square brackets, we report 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each managers as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 adds to the specification in column 2 the natural log of the number of days since the borrower's order started to control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

Table S.2: Tests of model predictions when excluding the first week of an order

	Number of workers borrowed		
	(1)	(2)	(3)
$(\%Abs\, i - \%Abs\, j)/2$	7.7340	5.8528	4.7662
	(2.5396) ∗∗∗	(1.8141) ∗∗∗	(1.7004) ∗∗∗
	[2.5140] ∗∗∗	[1.8040] ∗∗∗	[1.7013] ∗∗∗
	{2.9601} ∗∗∗	{2.0371} ∗∗∗	{2.0016} ∗∗
log(Maturity of relationship)	0.3780	1.4202	1.4343
	(0.1282) ∗∗∗	(0.0953) ∗∗∗	(0.0928) ∗∗∗
	[0.1311] ∗∗∗	[0.0969] ∗∗∗	[0.0946] ∗∗∗
	{0.1456} ∗∗∗	{0.1077} ∗∗∗	{0.1059} ∗∗∗
log(Distance)	−0.7595	−0.1275	−0.1254
	(0.1362) ∗∗∗	(0.0937)	(0.0916)
	[0.1382] ∗∗∗	[0.0946]	[0.0922]
	{0.1540} ∗∗∗	{0.1079}	{0.1048}
	Identity-based distance		
Different gender	−1.2557	−1.2863	−1.3414
	(0.2876) ∗∗∗	(0.2853) ∗∗∗	(0.2813) ∗∗∗
	[0.2899] ∗∗∗	[0.2974] ∗∗∗	[0.2950] ∗∗∗
	{0.3198} ∗∗∗	{0.3513} ∗∗∗	{0.3725} ∗∗∗
Different education	−0.4633	−0.1855	−0.2004
	(0.1351) ∗∗∗	(0.1054)∗	(0.1033)∗
	[0.1373] ∗∗∗	[0.1049]∗	[0.1028]∗
	{0.1145} ∗∗∗	{0.1107}∗	{0.1085}∗
log(Difference in age of managers)	−0.0303	−0.0520	−0.0532
	(0.0191)	(0.0226) ∗∗	(0.0224) ∗∗
	[0.0189]	[0.0221] ∗∗	[0.0219] ∗∗
	{0.0213}	{0.0248} ∗∗	{0.0249} ∗∗
log(Diff. in exp. on the line)	−0.1030	−0.2602	−0.2552
	(0.0958)	(0.0944) ∗∗∗	(0.0918) ∗∗∗
	[0.0951]	[0.0952] ∗∗∗	[0.0929] ∗∗∗
	{0.0820}	{0.1172} ∗∗	{0.1162} ∗∗
Observations	14918	14918	14918
Mean of Y	.189	.189	.189
SD	.758	.758	.758
Effect when X1= 1%	8.040000000000001 %	6.03 %	4.88 %
Effect when X1= 5%	47.21 %	34 %	26.91 %

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We exclude observations from borrowing lines that are in the first work-week of an order. We regress the daily number of workers borrowed at the manager-pair level on the average difference in absenteeism in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers are of different gender, a dummy for whether they have a different level of education, on their log age difference, and on their log difference in their experience managing their respective lines. We include dyads on a same floor for which the average difference in absenteeism in the pair is greater or equal to 0. In parentheses, we report standard errors clustered at the pair level. In square brackets, we report 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each managers as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 adds to the specification in column 2 the natural log of the number of days since the borrower's order started to control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

T Demographic Binary and Main Trading Partners

Table T.1: Tests of model predictions with a binary variable for any demographic difference

	Number of workers borrowed		
	(1)	(2)	(3)
$(\%Abs\ i - \%Abs\ j)/2$	5.7823	5.2853	4.9258
	(2.0215) $***$	(1.7566) $***$	(1.6720) $***$
	[2.0364] $***$	[1.7719] $***$	[1.6945] $***$
	{2.5917} $**$	{2.0397} $***$	{1.9709} $**$
log(Maturity of relationship)	0.3783	1.3090	1.3134
	(0.1157) $***$	(0.0845) $***$	(0.0840) $***$
	[0.1170] $***$	[0.0848] $***$	[0.0843] $***$
	{0.1349} $***$	{0.0892} $***$	{0.0888} $***$
log(Distance)	−0.8466	−0.3267	−0.3267
	(0.1223) $***$	(0.0922) $***$	(0.0922) $***$
	[0.1232] $***$	[0.0934] $***$	[0.0935] $***$
	{0.1618} $***$	{0.1248} $***$	{0.1251} $***$
Demographic distance	−0.4473	−0.3219	−0.3195
	(0.1817) $**$	(0.1576) $**$	(0.1578) $**$
	[0.1837] $**$	[0.1602] $**$	[0.1602] $**$
	{0.1872} $**$	{0.2046}	{0.2051}
Observations	27560	27560	27560
Mean of Y	.215	.215	.215
SD	.853	.853	.853
Effect when X1= 1%	5.95 %	5.43 %	5.05 %
Effect when X1= 5%	33.52 %	30.25 %	27.93 %

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress the daily number of workers borrowed at the manager-pair level on the average difference in absenteeism in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers have any demographic differences. More precisely, this variable equals 1 when managers are of different genders, or have a different level of education, or their age difference is above median, or their experience difference is above median. We include dyads on a same floor for which the average difference in absenteeism in the pair is greater or equal to 0. In parentheses, we report standard errors clustered at the pair level. In square brackets, we report 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each managers as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 has the same fixed effects as column 2, and we also control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

Table T.2: Tests of model predictions with a binary variable for whether the partner is a main partner

	Number of workers borrowed		
	(1)	(2)	(3)
$(\%Abs\ i - \%Abs\ j)/2$	5.7783	5.2232	4.8372
	(2.0030) ∗ ∗∗	(1.7450) ∗ ∗∗	(1.6579) ∗ ∗∗
	[2.0039] ∗ ∗∗	[1.7576] ∗ ∗∗	[1.6777] ∗ ∗∗
	{2.5540} ∗ ∗	{1.9998} ∗ ∗∗	{1.9313} ∗ ∗
log(Maturity of relationship)	0.2441	1.2077	1.2116
	(0.1022) ∗ ∗	(0.0893) ∗ ∗∗	(0.0887) ∗ ∗∗
	[0.1031] ∗ ∗	[0.0899] ∗ ∗∗	[0.0893] ∗ ∗∗
	{0.1165} ∗ ∗	{0.0937} ∗ ∗∗	{0.0939} ∗ ∗∗
log(Distance)	−0.5467	−0.1532	−0.1529
	(0.0961) ∗ ∗∗	(0.0832)∗	(0.0830)∗
	[0.0975] ∗ ∗∗	[0.0847]∗	[0.0845]∗
	{0.1027} ∗ ∗∗	{0.0995}	{0.0990}
Main partner	0.9719	0.4123	0.4121
	(0.1556) ∗ ∗∗	(0.1208) ∗ ∗∗	(0.1208) ∗ ∗∗
	[0.1550] ∗ ∗∗	[0.1197] ∗ ∗∗	[0.1198] ∗ ∗∗
	{0.1905} ∗ ∗∗	{0.1349} ∗ ∗∗	{0.1356} ∗ ∗∗
	Identity-based distance		
Different gender	−0.7073	−0.9035	−0.9075
	(0.1721) ∗ ∗∗	(0.1814) ∗ ∗∗	(0.1834) ∗ ∗∗
	[0.1603] ∗ ∗∗	[0.1755] ∗ ∗∗	[0.1780] ∗ ∗∗
	{0.3049} ∗ ∗	{0.3400} ∗ ∗∗	{0.3425} ∗ ∗∗
Different education	−0.3885	−0.1559	−0.1560
	(0.1047) ∗ ∗∗	(0.0868)∗	(0.0866)∗
	[0.1069] ∗ ∗∗	[0.0880]∗	[0.0879]∗
	{0.1183} ∗ ∗∗	{0.0895}∗	{0.0891}∗
log(Difference in age of managers)	−0.0320	−0.0506	−0.0506
	(0.0187)∗	(0.0160) ∗ ∗∗	(0.0160) ∗ ∗∗
	[0.0186]∗	[0.0159] ∗ ∗∗	[0.0159] ∗ ∗∗
	{0.0208}	{0.0172} ∗ ∗∗	{0.0174} ∗ ∗∗
log(Diff. in exp. on the line)	−0.2310	−0.2866	−0.2870
	(0.0898) ∗ ∗	(0.0775) ∗ ∗∗	(0.0772) ∗ ∗∗
	[0.0892] ∗ ∗∗	[0.0764] ∗ ∗∗	[0.0761] ∗ ∗∗
	{0.0778} ∗ ∗∗	{0.0777} ∗ ∗∗	{0.0774} ∗ ∗∗
Observations	27560	27560	27560
Mean of Y	.215	.215	.215
SD	.853	.853	.853
Effect when X1= 1%	5.95 %	5.36 %	4.96 %
Effect when X1= 5%	33.5 %	29.84 %	27.36 %

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We regress the daily number of workers borrowed at the manager-pair level for main partners on the average difference in absenteeism in the pair, the natural log of the maturity of the relationship, the log physical distance in feet, a dummy for whether the managers are of different gender, a dummy for whether they have a different level of education, on their log age difference, and on their log difference in their experience managing their respective lines. We include dyads on a same floor for which the average difference in absenteeism in the pair is greater or equal to 0. In parentheses, we report standard errors clustered at the pair level. In square brackets, we report 2-way clustered standard errors with one cluster for pairs and one cluster for the date. In curly brackets, we report 2-way clustered standard errors with one cluster for each line. In column 1, we include fixed effects for each managers as well as unit fixed effects. In column 2, we additionally include year, month, and day of the week fixed effects. Column 3 has the same fixed effects as column 2, and we also control for learning-by-doing by including the natural log of the number of days since the borrower's order started.

U Instrumental Variable

Some factors may jointly affect absenteeism and efficiency. For example, previous studies from this empirical context have shown that efficiency is impacted by temperature (Adhvaryu et al., 2020b) and air pollution (Adhvaryu et al., 2021b). It is also possible that on excessively hot or polluted days more workers decide to stay home. Similarly, a manager may attempt to increase his line's productivity by treating workers harshly or react to poor productivity by scolding workers, driving up absenteeism.

In order to account for such potential endogeneity or reverse causality, we instrument for absenteeism using the number of home line workers from a state with a major religious festival on a given day. Although most workers are Hindu and many Hindu festivals are common across India, they are often celebrated at different dates in different regions of the country. Moreover, the importance given to different deities is highly heterogeneous across different regions of the country and, as a result, there is much variation in the timing and intensity of festival celebrations. To construct our instrument, we assume that workers are from the state where their native language or dialect is primarily spoken.[165] We compile the dates of all major Hindu festivals across all Indian states. For each line, we define the proportion of their home line workers that are from a state with a festival at a given date as our instrument.[166]

[165] In our data, we do not know where workers are from, but we know the language they speak. Although dialects are highly segregated across the country, the workers may not necessarily originate from that state. Nevertheless, the workers are likely to celebrate the festivals from that state since language is highly associated with cultural events.

[166] To compile the festival dates, we relied on government sources as much as possible. We compiled the dates of every major festivals celebrated state-wise (that we could find). In most cases, state governments list the most important festivals of their respective state. In some cases however, all festivals, major and minor, were listed. In such case, we retained only the festivals for which there was an actual holiday mandated by the government. The celebration dates of most festivals change with the lunar calendar and they often are celebrated for a different length of time. We used Google history searches to find the dates of

Managers may anticipate absenteeism for more common festivals like Diwali and plan accordingly. However, workers on any given line come from all over the country. As a result, it is unlikely that managers can anticipate absenteeism stemming from every festival.[167] Indeed, on any given day, an average of nearly 8 workers on a line with roughly 55 home line workers hails from a state celebrating some major, government recognized festival that day.

Table U.1 is the instrumental variable version of the specification presented in Table 13, column 3. The instrument is highly predictive of absenteeism as shown in the first stage panel and coefficients from the IV second stage are quite similar to the coefficients from the OLS regressions. This suggests that, conditional on the fixed effects included, idiosyncratic line-level daily absenteeism is as good as random. Indeed, the Hausman test statistic reported in the lower panel confirms that we cannot reject that the OLS and IV coefficients are the same.

To confirm that the relationship between workers present on the line and efficiency depicted in Figure 8, panel (b), is preserved when leveraging the variation in absenteeism derived from the instrument, we plot the reduced form relationship using a nonparametric IV fit in Figure U.1. That is, we first compute the average efficiency at the line level by 1% bins of the percentage of workers on the line just as we did in Figure 8, panel (b). For each of these bins, we also construct the average number of home line workers with a festival at the line level. Following (Chetverikov and Wilhelm, 2017), we let the efficiency depend on a flexible spline in the percentage of workers on the line. This flexible spline is in return being instrumented with a flexible spline in

the festivals in 2013 and 2014.

[167] We also included major Muslim festivals since a minority of workers are Muslim. Muslim festival dates are common across the country, but the worker composition at the line level is still varied enough to make it hard for managers to anticipate all absenteeism due to festivals.

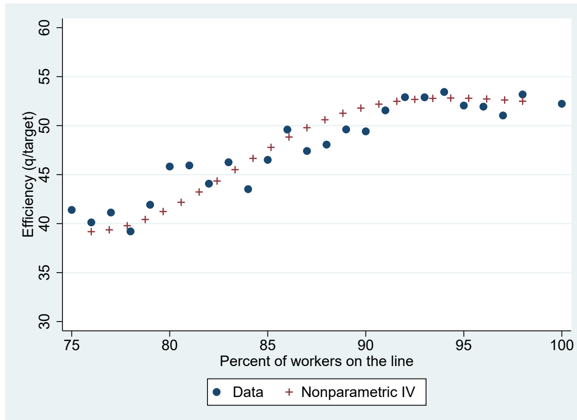
the number of home line workers with a festival in a fashion similar to a 2SLS estimator. The dots in Figure U.1 depict the uninstrumented relationship and the crosses depict the fitted values of the nonparametric IV estimator. We can see that instrumented pattern closely matches the raw pattern. The same can be said about the production function as can be seen from Figure U.2.

Table U.1: Productivity losses from absenteeism with instrument

	IV-Second stage: Efficiency (%)
	(1)
Percentage of Workers Absent	-0.4814
	(0.2241) ∗∗
	[0.2514]∗
	IV-First stage: Percentage of Workers Absent
Number of Workers with Festival	0.0255
	(0.0039) ∗∗∗
	[0.0054] ∗∗∗
Observations	10797
Mean of Y	49.086
SD	15.847
Kleibergen-Paap F	22.46
Hausman test p-value	.61

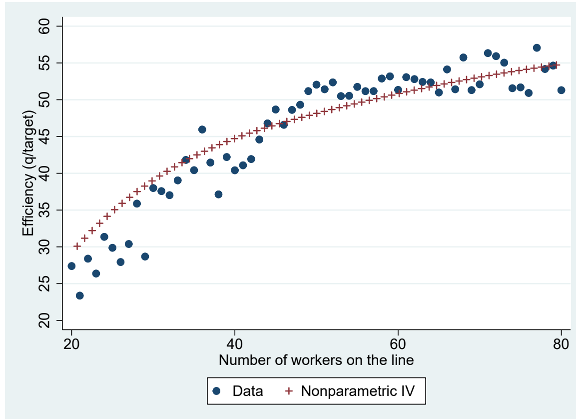
Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. We estimate a 2SLS with efficiency at the line day level as the dependent variable. Absenteeism at the line day level is the endogenous regressor that we instrument using the number of home line workers with a festival that day. We cluster the standard errors reported in parentheses at the manager level and at the manager and date level in square brackets. We regress efficiency on the percentage of workers absent and we instrument this variable by the number of workers on the line with a festival that day.

Figure U.1: Average efficiency by percentage of workers present on the line with nonparametric IV fit



Note: We compute the average efficiency of the workers on the line and the average number of home line workers with a festival by the percentage of workers working on the line (in 1% bins). The percentage of workers on the line is measured relative to the number of home line workers available. We let the average efficiency depend on a spline with 3 equally-spaced knots in the average percentage of workers on the line. This spline is instrumented with a spline with 4 equally-spaced knots in the average number of home line workers with a festival in a fashion similar to a 2SLS estimator. The dots depict the uninstrumented relationship and the crosses depict the fitted values of the nonparametric IV estimator. We exclude cases where the percentage of workers on the line falls below 75% or above 100% from the figure as these cases are infrequent.

Figure U.2: Production function with nonparametric IV fit

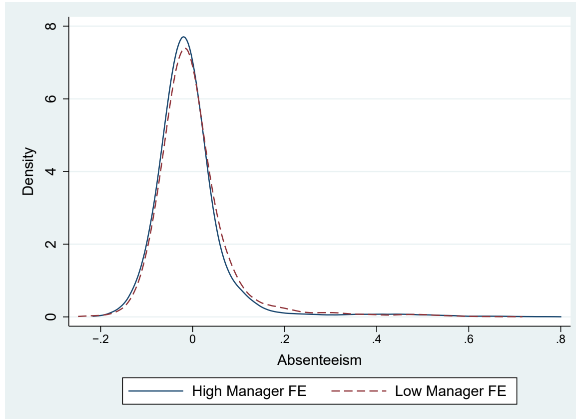


Note: We compute the average efficiency of the workers on the line and the average number of home line workers with a festival by the number of workers working on the line (in 1% bins). We let the average efficiency depend on a spline with 3 equally-spaced knots in the average percentage of workers on the line. This spline is instrumented with a spline with 4 equally-spaced knots in the average number of home line workers with a festival in a fashion similar to a 2SLS estimator. The dots depict the uninstrumented relationship and the crosses depict the fitted values of the nonparametric IV estimator. We exclude cases where the percentage of workers on the line falls below 75% or above 100% from the figure as these cases are infrequent.

Last, we check that the incidence of absenteeism shocks is balanced across lines and managers of varying quality. Using worker-by-day data, we recover manager (and worker) fixed effects through a decomposition in the spirit of (Abowd et al., 1999). To do so, we regress the log efficiency on unit, year, month, date, and style fixed effects and recover the manager component. We classify managers with a component higher or equal to the median as high efficiency managers and those below the median as low efficiency managers.

Then, in Figure U.3, we partial out the same fixed effects from manager-day absenteeism and plot the distribution of residual absenteeism against the managers' efficiency status. "*Better*" and "*worse*" managers face nearly identical absenteeism shock distributions.

Figure U.3: Distribution of residual absenteeism by manager FE



Note: We regress the log efficiency on unit, year, month, date, and style fixed effects and recover the managers' component. We classify managers with a component higher or equal to the median as high efficiency managers and those below the median as low efficiency managers. We partial out the same fixed effects from manager-day absenteeism and plot the distribution of residual absenteeism against the managers' efficiency status. Both types of managers have very similar absenteeism distributions. The mean residual absenteeism is -0.002 for high-efficiency managers and 0.004 for low-efficiency managers. The standard deviations are virtually identical (0.089).

V Proofs

Proof of Proposition 1. A stationary symmetric optimal relational contract, $\boldsymbol{\theta}^*$, is defined as the the value of θ that maximizes $U^R(\cdot)$,

$$\begin{aligned}(1-\delta)U^R(\boldsymbol{\theta}) = & \sum_{\{(i,j)|y_i>\max\{y_j,\alpha_{ij}\}\}} \pi_{ij}\left[f(y_i-\theta_{ij})-c_{ij}\right] \\ & + \sum_{\{(i,j)|y_j>\max\{y_i,\alpha_{ij}\}\}} \pi_{ij}\left[f(y_j-\theta_{ji})\right] \\ & + \sum_{\{(i,j)|y_j\leq y_i<\alpha_{ij}\}} \pi_{ij} f(y_i) + \sum_{\{(i,j)|y_i<y_j\leq\alpha_{ij}\}} \pi_{ij} f(y_i),\end{aligned} \tag{V.1}$$

subject to the incentive compatibility constraint (13). The existence and uniqueness of $\boldsymbol{\theta}^*$ follows from the maximization of a concave function, $U^R(\cdot)$, over a compact convex subset of $\mathbb{R}^d$.

First, note that the concavity of $U^R(\cdot)$ follows from the concavity of f (i.e., $f'' < 0$), restricted to all symmetric non-negative allocations such that (13) is satisfied. Second, note that the domain,

$$\Omega := [-\overline{y}, \overline{y}]^d \cap \left[\cap_{i=1}^{n} \cap_{j=1}^{i-1} \underbrace{\left\{ \theta_{ij} \in \mathbb{R}^d | f\left(y_i\right) - f\left(y_i - \theta_{ij}\right) + c_{ij} \leq \delta \left(U^R\left(\boldsymbol{\theta}\right) - V \right) \right\}}_{=:A} \right],$$

is a convex and compact subset of $\mathbb{R}^d$ since A is closed and convex.

To characterize $\boldsymbol{\theta}^*$, let $H(y, c, w)$ a function implicitly defined by

$$f(y) + c - w = f(y - H(y, c, w)). \tag{V.2}$$

Note that $f'(\cdot) > 0$, then $H(\cdot)$ can be expressed as

$$H(y, c, w) = y - f^{-1}(c - w + f(y)), \tag{V.3}$$

for all the values (y, c, w) for which $c - w + f(y) > 0$. Given y_i, c_{ij} and $\delta \left(U^R\left(\boldsymbol{\theta}^*\right) - V \right)$ then $H(\cdot)$ is such that

$$f(y_i) - f\left(y_i - H\left(y_i, c_{ij}, \delta\left(U^R\left(\boldsymbol{\theta}^*\right) - V\right)\right) \right) + c_{ij} = \delta\left(U^R\left(\boldsymbol{\theta}^*\right) - V\right), \tag{V.4}$$

as long as

$$f(y_i) + c_{ij} > \delta \left(U^R \left(\boldsymbol{\theta}^* \right) - V \right) \tag{V.5}$$

is satisfied. Therefore, $\theta_{ij}^* = H \left(y_i, c_{ij}, \delta \left(U^R \left(\boldsymbol{\theta}^* \right) - V \right) \right)$ if (V.5) is satisfied.

Now we show that $\theta_{ij}^* = \min \left\{ \hat{\theta}_{ij}, H \left(y_i, c_{ij}, \delta \left(U^R \left(\boldsymbol{\theta}^* \right) - V \right) \right) \right\}$. We split the proof in two cases: *i)* suppose that $\hat{\theta}_{ij} > H \left(y_i, c_{ij}, \delta \left(U^R \left(\boldsymbol{\theta}^* \right) - V \right) \right)$, then in this case we show that $\theta_{ij}^* = H \left(y_i, c_{ij}, \delta \left(U^R \left(\boldsymbol{\theta}^* \right) - V \right) \right)$; *ii)* suppose that $\hat{\theta}_{ij} \leq H \left(y_i, c_{ij}, \delta \left(U^R \left(\boldsymbol{\theta}^* \right) - V \right) \right)$ then we show that $\theta_{ij}^* = \hat{\theta}_{ij}$.

i) Suppose that $\hat{\theta}_{ij} > H \left(y_i, c_{ij}, \delta \left(U^R \left(\boldsymbol{\theta}^* \right) - V \right) \right)$. Since $H(y_i, c_{ij}, \delta \left(U^R \left(\boldsymbol{\theta}^* \right) - V \right)) = y_i - f^{-1}(c_{ij} - \delta \left(U^R \left(\boldsymbol{\theta}^* \right) - V \right) + f(y_i))$ it follows that

$$\begin{aligned}
\hat{\theta}_{ij} > H \left(y_i, c_{ij}, \delta \left(U^R \left(\boldsymbol{\theta}^* \right) - V \right) \right) &\iff \\
\hat{\theta}_{ij} > y_i - f^{-1}(c_{ij} - \delta \left(U^R \left(\boldsymbol{\theta}^* \right) - V \right) + f(y_i)) &\iff \\
c_{ij} - \delta \left(U^R \left(\boldsymbol{\theta}^* \right) - V \right) + f(y_i) > f(y_i - \hat{\theta}_{ij}) &\iff \\
f(y_i) - f(y_i - \hat{\theta}_{ij}) + c_{ij} > \delta \left(U^R \left(\boldsymbol{\theta}^* \right) - V \right). &
\end{aligned}$$

Note that $f > 0$, then

$$f(y_i) + c_{ij} > \delta \left(U^R \left(\boldsymbol{\theta}^* \right) - V \right).$$

Thus, (V.5) is satisfied, and we conclude that $\theta_{ij}^* = H \left(y_i, c_{ij}, \delta \left(U^R \left(\boldsymbol{\theta}^* \right) - V \right) \right)$.

ii) Suppose that $\hat{\theta}_{ij} \leq H\left(y_i, c_{ij}, \delta\left(U^R\left(\boldsymbol{\theta}^*\right) - V\right)\right)$. From the definition of $H(\cdot)$ we get

$$\begin{aligned}
\hat{\theta}_{ij} \leq H\left(y_i, c_{ij}, \delta\left(U^R\left(\boldsymbol{\theta}^*\right) - V\right)\right) &\iff \\
\hat{\theta}_{ij} \leq y_i - f^{-1}(c_{ij} - \delta\left(U^R\left(\boldsymbol{\theta}^*\right) - V\right) + f(y_i)) &\iff \\
c_{ij} - \delta\left(U^R\left(\boldsymbol{\theta}^*\right) - V\right) + f(y_i) \leq f(y_i - \hat{\theta}_{ij}) &\iff \\
f(y_i) - f(y_i - \hat{\theta}_{ij}) + c_{ij} \leq \delta\left(U^R\left(\boldsymbol{\theta}^*\right) - V\right). &
\end{aligned}$$

Therefore, the contract defined by $\boldsymbol{\theta}^*/\hat{\theta}_{ij}$ belongs to the set Ω.[168] Note that

$$\frac{\partial U^R\left(\boldsymbol{\theta}\right)}{\partial \theta_{ij}} > (<)\, 0 \;\text{ if }\; \theta_{ij} < (>)\, \hat{\theta}_{ij}. \tag{V.6}$$

Thus, if $\theta^*_{ij} < \hat{\theta}_{ij}$ then $U^R(\boldsymbol{\theta}^*) < U^R(\boldsymbol{\theta}^*/\hat{\theta}_{ij})$. If $\theta^*_{ij} > \hat{\theta}_{ij}$ then $U^R(\boldsymbol{\theta}^*) < U^R(\boldsymbol{\theta}^*/\hat{\theta}_{ij})$. Note that $\boldsymbol{\theta}^*/\hat{\theta}_{ij}$ yields a larger utility than $\boldsymbol{\theta}^*$, with $\boldsymbol{\theta}^*/\hat{\theta}_{ij} \in \Omega$, which is a contradiction. Therefore, $\theta^*_{ij} = \hat{\theta}_{ij}$.

Thus, we conclude that that $\theta^*_{ij} = \min\left\{\hat{\theta}_{ij}, H\left(y_i, c_{ij}, \delta\left(U^R\left(\boldsymbol{\theta}^*\right) - V\right)\right)\right\}$.

Proof of Proposition 2. An optimal dynamic relational contract, $\{\boldsymbol{\theta}^*_t\}_{t\in\mathbb{N}}$, is defined as the value of $\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}$ that maximizes $U^R_0\left(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}; \gamma_0\right)$ subject to the incentive compatibility constraints (12) for all t, where $U^R_0\left(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}; \gamma_0\right)$ is the present value of the expected utility over time, defined in equation (V.10). We show that there exists $\underline{\theta} > 0$ such that if $\{\boldsymbol{\theta}^*_t\}_{t\in\mathbb{N}}$ is an optimal dynamic relational contract satisfying that for any $i, j \in \mathcal{K}$, and for every $t \in \mathbb{N}$, $\theta^*_{ij,t} \in (\underline{\theta}, \hat{\theta}_{ij})$, then $\{\boldsymbol{\theta}^*_t\}_{t\in\mathbb{N}}$ must be monotonic.[169]

[168] $\boldsymbol{\theta}^*/\hat{\theta}_{ij}$ is notation for the vector $\boldsymbol{\theta}^*$ in which the θ^*_{ij} is replaced by $\hat{\theta}_{ij}$

[169] A dynamic relational contract $\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}$ is monotonic if for for any $i, j \in \mathcal{K}$, and for every $t \in \mathbb{N}$, $\theta_{ij,t} \leq \theta_{ij,t+1}$.

We divide the proof in two steps: 1) we find an expression for the present value of the expected utility over time at time t, $U_t^R\left(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}};\gamma_t\right)$; 2) we show that $U_t^R\left(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}};\gamma_t\right)$ is increasing with respect to γ_t.[170]

1) Given a relational contract $\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}$ and the beliefs at time t, γ_t, an R-type manager's expected utility after t periods is

$$\begin{aligned}
U_t\left(\boldsymbol{\theta}_t;\gamma_t\right) = \left(\gamma_t + \left(1-\gamma_t\right)\rho\right)&\left[\sum_{S_1}\pi_{ij}\left(f\left(y_{i,t}-\theta_{ij,t}\right)-c_{ij}\right)+\sum_{S_2}\pi_{ij}f\left(y_{j,t}+\theta_{ij,t}\right)\right]\\
&+\left(1-\gamma_t\right)\left(1-\rho\right)\left[\sum_{S_1}\pi_{ij}f\left(y_{i,t}\right)+\sum_{S_2}\pi_{ij}f\left(y_{j,t}\right)\right]+\sum_{S_3\cup S_4}\pi_{ij}f\left(y_{i,t}\right)\\
&+\left(1-\gamma_t\right)\left(1-\rho\right)\delta V+\left(\gamma_t+\left(1-\gamma_t\right)\rho\right)\delta U_{t+1}\left(\boldsymbol{\theta}_{t+1};\gamma_{t+1}\right),
\end{aligned} \tag{V.7}$$

where $S_1 \equiv \{(i,j)|y_{i,t} > \max\{y_{j,t},\alpha_{ij,t}\}\}$, $S_2 \equiv \{(i,j)|y_{j,t} > \max\{y_{i,t},\alpha_{ji,t}\}\}$, $S_3 \cup S_4 \equiv \{(i,j)|y_{j,t} \leq y_{i,t} < \alpha_{ij,t}\} \cup \{(i,j)|y_{i,t} < y_{j,t} \leq \alpha_{ji,t}\}$, and $\alpha_{ij,t}$ is the value of y_i such that

$$f(y_i) - f(y_i - \theta_{ij,t}) + c_{ij} - \delta\left(U_{t+1}^R\left(\boldsymbol{\theta}_{t+1};\gamma_{t+1}\right) - V\right) = 0, \tag{V.8}$$

is satisfied for positive values of $\theta_{ij,t}$ and $\theta_{ij,t+1}$.[171]

To simplify the notation let

$$\tilde{\gamma}_t = \gamma_t + \left(1-\gamma_t\right)\rho \quad \text{ and } \quad 1-\tilde{\gamma}_t = \left(1-\gamma_t\right)\left(1-\rho\right).$$

[170] Note that in this proof we are using the fact that both the beliefs γ_t^{ij} and the probabilities π_{ij} are symmetric. Thus, we omit the index i in the utility of an R-type manager.

[171] At time t, the set S_1 (S_2) is the set of states of manager i (j) better than the state of manager j (i) and high enough to compensate for the transaction costs; S_3 (S_4) is the set of states of manager i (j) better than the states of manager j (i), but are not high enough to compensate for the transaction costs, thus, there are no trades.

To find $U_t^R(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}};\gamma_t)$, we will recursively apply (V.7). The term $\tilde{\gamma}_t$ in the expression (V.7) is capturing R-type manager's utility when interacting with the mass of reliable managers γ_t, and the mass of unreliable managers telling the true $(1-\gamma_t)\rho$. Then, $U_t^R(\boldsymbol{\theta}_t;\gamma_t)$ can be expressed as

$$U_t^R(\boldsymbol{\theta}_t;\gamma_t) = \tilde{\gamma}_t F(\boldsymbol{\theta}_t) + C(V;\gamma_t) + g(\boldsymbol{y};\gamma_t) + \tilde{\gamma}_t \delta U_{t+1}^R(\boldsymbol{\theta}_{t+1};\gamma_{t+1}), \qquad \text{(V.9)}$$

where

$$\begin{aligned}
F(\boldsymbol{\theta}_t) &\equiv \sum_{S_1} \pi_{ij}\left[f(y_i-\theta_{ij,t}) + f(y_j+\theta_{ij,t})\right],\\
C(V;\gamma_t) &\equiv -\tilde{\gamma}_t \sum_{S_1} \pi_{ij} c_{ij} + (1-\tilde{\gamma}_t)\,\delta V, \text{ and}\\
g(\boldsymbol{y};\gamma_t) &\equiv (1-\tilde{\gamma}_t)\sum_{S_1}\pi_{ij}\left[f(y_i)+f(y_j)\right] + \sum_{S_3\cup S_4}\pi_{ij} f(y_i).
\end{aligned}$$

Note that (V.9) follows from: (i) $\pi_{ij}=\pi_{ji}$ for all $i,j\in\mathcal{K}$; (ii) $\pi_{ij}=\mathbb{P}(y_{i,t}=y_i)\mathbb{P}(y_{j,t}=y_j)$ for each t; (iii) since beliefs are symmetric $\alpha_{ij,t}=\alpha_{ji,t}$ and $S_1=S_2$. Now, we successively use (V.9) to obtain an explicit equation for $U_t^R(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}};\gamma_t)$. Note that after two iterations we have

$$\begin{aligned}
U_t^R(\boldsymbol{\theta}_t;\gamma_t) =& \tilde{\gamma}_t\left[F(\boldsymbol{\theta}_t) + \delta\tilde{\gamma}_{t+1}F(\boldsymbol{\theta}_{t+1}) + \delta^2\tilde{\gamma}_{t+1}\tilde{\gamma}_{t+2}F(\boldsymbol{\theta}_{t+2})\right]\\
&+\left[C(V;\gamma_t) + \delta\tilde{\gamma}_t C(V;\gamma_{t+1}) + \delta^2\tilde{\gamma}_t\tilde{\gamma}_{t+1}C(V;\gamma_{t+2})\right]\\
&+\left[g(\boldsymbol{y};\gamma_t) + \delta\tilde{\gamma}_t g(\boldsymbol{y};\gamma_{t+1}) + \delta^2\tilde{\gamma}_t\tilde{\gamma}_{t+1}g(\boldsymbol{y};\gamma_{t+2})\right] + \tilde{\gamma}_t\tilde{\gamma}_{t+1}\tilde{\gamma}_{t+2}\delta^3 U_{t+3}^R(\boldsymbol{\theta}_{t+3};\gamma_{t+3}).
\end{aligned}$$

Thus, the present value of the expected utility at time t is

$$U_t^R\left(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}};\gamma_t\right)=\sum_{k=0}^{\infty}\delta^k\Gamma_t^{k-1}\left[\tilde{\gamma}_{t+k}F\left(\boldsymbol{\theta}_{t+k}\right)+C\left(V;\gamma_{t+k}\right)+g\left(\boldsymbol{y};\gamma_{t+k}\right)\right], \tag{V.10}$$

where $\Gamma_t^k := \prod_{l=0}^k \tilde{\gamma}_{t+l}$, and $\Gamma_t^{-1} := 1$.

2) We show now that $U_t^R\left(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}};\gamma_t\right)$ is increasing with respect to γ_t. First, note that $F(\cdot)$ has a global maximum at $\theta_{ij,t}=\hat{\theta}_{ij}$, thus, for any $(i,j)\in S_1$

$$\frac{\partial F\left(\boldsymbol{\theta}_t\right)}{\partial\theta_{ij,t}}>(<)\,0\quad\text{if}\quad\theta_{ij,t}<(>)\,\hat{\theta}_{ij}. \tag{V.11}$$

Therefore, $F\left(\boldsymbol{\theta}_t\right)$ is strictly positive and bounded above by $F(\hat{\boldsymbol{\theta}})$. Second, note that for any $k,t\in\mathbb{N}$ the following facts hold true:

(i) $\gamma_t=\dfrac{\gamma_0}{\gamma_0+(1-\rho)^t\left(1-\gamma_0\right)}$.

(ii) Let $h\left(x\right)=\dfrac{x}{x+\left(1-x\right)\left(1-\rho\right)}$. Then $\gamma_{t+k}=h^k\left(\gamma_t\right)=\cdots=h^{k+t}\left(\gamma_0\right)$.

(iii) From the definition of $\tilde{\gamma}_{t+k}$, and the fact $h'(\cdot)>0$, $\dfrac{\partial\tilde{\gamma}_{t+k}}{\partial\gamma_t}=\left(1-\rho\right)\dfrac{\partial h^k\left(\gamma_t\right)}{\partial\gamma_t}>0$.

(iv) Since $\ln\Gamma_t^k=\sum_{l=0}^{k}\ln\tilde{\gamma}_{t+l}$, then $\dfrac{\partial\Gamma_t^k}{\partial\gamma_t}=\Gamma_t^k\sum_{l=0}^{k}\dfrac{1}{\tilde{\gamma}_{t+l}}\dfrac{\partial\tilde{\gamma}_{t+l}}{\partial\gamma_t}>0$.

(V.12)

The derivative of $U_t^R\left(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}};\gamma_t\right)$ with respect to γ_t is another series with the k-term equal to

$$
\begin{aligned}
&\frac{\partial}{\partial\gamma_t}\left\{\Gamma_t^{k-1}\left[\tilde{\gamma}_{t+k}F\left(\boldsymbol{\theta}_{t+k}\right)+C\left(V;\gamma_{t+k}\right)+g\left(\boldsymbol{y};\gamma_{t+k}\right)\right]\right\}\\
&=\Gamma_t^{k-1}\left(\sum_{l=0}^{k}\frac{\tilde{\gamma}_{t+k}}{\tilde{\gamma}_{t+l}}\frac{\partial\tilde{\gamma}_{t+l}}{\partial\gamma_t}\right)\left(\sum_{S_1}\pi_{ij}\left[f\left(y_i-\theta_{ij,t+k}\right)+f\left(y_j+\theta_{ij,t+k}\right)-f\left(y_i\right)-f\left(y_j\right)-c_{ij}\right]\right)\\
&+\Gamma_t^{k-1}\left(\sum_{l=0}^{k-1}\frac{\left(1-\tilde{\gamma}_{t+k}\right)}{\tilde{\gamma}_{t+l}}\frac{\partial\tilde{\gamma}_{t+l}}{\partial\gamma_t}-\frac{\partial\tilde{\gamma}_{t+k}}{\partial\gamma_t}\right)\delta V+\Gamma_t^{k-1}\left(\sum_{l=0}^{k-1}\frac{1}{\tilde{\gamma}_{t+l}}\frac{\partial\tilde{\gamma}_{t+l}}{\partial\gamma_t}\right)E_{\pi_{ij}}\left[f\left(y_i\right)\right],
\end{aligned}
\tag{V.13}
$$

where $E_{\pi_{ij}}\left[f\left(y_i\right)\right]=\sum_{S_1}\pi_{ij}\left[f\left(y_i\right)+f\left(y_j\right)\right]+\sum_{S_3\cup S_4}\pi_{ij}f\left(y_i\right)$.[172]

From (iii) and (iv) in (V.12), expression (V.13), is positive for any $k\in\mathbb{N}\cup\{0\}$ as long as

$$
\sum_{S_1}\pi_{ij}\left[f\left(y_i-\theta_{ij,t+k}\right)+f\left(y_j+\theta_{ij,t+k}\right)-f\left(y_i\right)-f\left(y_j\right)-c_{ij}\right]-\delta V>0.
\tag{V.15}
$$

Now, the left hand side of (V.15) is strictly increasing with respect to the variable $\theta_{ij,t+k}$, as long as $\theta_{ij,t+k}<\hat{\theta}_{ij}$. Moreover, if $\theta_{ij,t+k}=\hat{\theta}_{ij}$ the left hand side of (V.15) is

$$
\sum_{S_1}\pi_{ij}\left[2f\left(\frac{y_i+y_j}{2}\right)-f\left(y_i\right)-f\left(y_j\right)-c_{ij}\right]-\delta V>0.
\tag{V.16}
$$

By continuity there exists a constant $\underline{\theta}$, independent of k, such that for any $\theta_{ij,t+k}\in(\underline{\theta},\hat{\theta}_{ij})$, (V.15) holds. Which proves that expression (V.13) is positive

[172]Note that for $k=0$, (V.13) is

$$
\begin{aligned}
&\frac{\partial}{\partial\gamma_t}\left[\tilde{\gamma}_tF\left(\boldsymbol{\theta}_t\right)+C\left(V;\gamma_t\right)+g\left(\boldsymbol{y};\gamma_t\right)\right]\\
&=(1-\rho)\sum_{S_1}\pi_{ij}\left[f\left(y_i-\theta_{ij,t}\right)+f\left(y_j+\theta_{ij,t}\right)-f\left(y_i\right)-f\left(y_j\right)-c_{ij}\right]-(1-\rho)\delta V.
\end{aligned}
\tag{V.14}
$$

for any $k \in \mathbb{N} \cup \{0\}$, thus, $U_t^R(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}; \gamma_t)$ is strictly increasing with respect to γ_t.

Finally, if $\{\boldsymbol{\theta}_t^*\}_{t\in\mathbb{N}}$ is an optimal dynamic relational contract satisfying that for any $i, j \in \mathcal{K}$, and for every $t \in \mathbb{N}$, $\theta_{ij,t}^* \in (\underline{\theta}, \hat{\theta}_{ij})$, then $\{\boldsymbol{\theta}_t^*\}_{t\in\mathbb{N}}$ is a maximum of the function $U_0^R(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}; \gamma_0)$ subject to the IC constraints. Note that the IC constraint increases at every step t, then by the monotonicity of $U_t^R(\{\boldsymbol{\theta}_t\}_{t\in\mathbb{N}}; \gamma_t)$ and (V.11), $\{\boldsymbol{\theta}_t^*\}_{t\in\mathbb{N}}$ must be monotonic.

Proof of Prediction 1. Let $y_i^1 > y_i^2 > y_j$ be three different home line levels in $\{y_1, \ldots, y_n\}$. Let θ_{ij}^1 and θ_{ij}^2 be the respective optimal allocations from the stationary contract $\boldsymbol{\theta}^*$. Given that the first best allocation $\hat{\theta}$ is never achieved, then $\theta_{ij}^1 < \hat{\theta}_{ij}^1$ and $\theta_{ij}^2 < \hat{\theta}_{ij}^2$. From Proposition 1,

$$\theta_{ij}^1 = H\left(y_i^1, c_{ij}, \delta\left(U^R(\boldsymbol{\theta}^*) - V\right)\right),$$

and

$$\theta_{ij}^2 = H\left(y_i^2, c_{ij}, \delta\left(U^R(\boldsymbol{\theta}^*) - V\right)\right).$$

We show that $\theta_{ij}^1 > \theta_{ij}^2$. From equation (V.3) it follows that H is strictly increasing on y as long as $w > c$. Since $y_i^l > y_j$ for $l = 1, 2$ then $\theta_{ij}^l > 0$ and because

$$\theta_{ij}^l > 0 \iff f(y_i^l) - f(y_i^l - \theta_{ij}^l) > 0,$$

we have that $\delta\left(U^R\left(\boldsymbol{\theta}^*\right)-V\right)>c_{ij}$. Thus, H is strictly increasing with respect to y and

$$\theta_{ij}^1=H(y_i^1,c_{ij},\delta\left(U^R\left(\boldsymbol{\theta}^*\right)-V\right))>H(y_i^2,c_{ij},\delta\left(U^R\left(\boldsymbol{\theta}^*\right)-V\right))=\theta_{ij}^2,$$

concluding the proof.

Proof of Prediction 2. Let $c_{ij}^1<c_{ij}^2$ two different transaction cost. If θ_{ij}^1 and θ_{ij}^2 are the stationary relational contracts associated with each c_{ij}^1, c_{ij}^2, respectively, then we show that $\theta_{ij}^1>\theta_{ij}^2$. Given that the first best allocation $\hat{\theta}$ is never achieved for c_{ij}^1 nor c_{ij}^2, then $\theta_{ij}^1<\hat{\theta}_{ij}$ and $\theta_{ij}^2<\hat{\theta}_{ij}$. From Proposition 1

$$\theta_{ij}^1=H\left(y_i,c_{ij}^1,\delta\left(U^R\left(\boldsymbol{\theta}^1\right)-V\right)\right),$$

and

$$\theta_{ij}^2=H\left(y_i,c_{ij}^2,\delta\left(U^R\left(\boldsymbol{\theta}^2\right)-V\right)\right).$$

Note that

$$\begin{aligned}&\underbrace{\left\{\theta_{ij}\in\mathbb{R}^d|f\left(y_i\right)-f\left(y_i-\theta_{ij}\right)+c_{ij}^2\leq\delta\left(U^R\left(\boldsymbol{\theta}\right)-V\right)\right\}}_{A_2}\\&\subseteq\underbrace{\left\{\theta_{ij}\in\mathbb{R}^d|f\left(y_i\right)-f\left(y_i-\theta_{ij}\right)+c_{ij}^1\leq\delta\left(U^R\left(\boldsymbol{\theta}\right)-V\right)\right\}}_{A_1},\end{aligned}$$

which implies that $\Omega_2\subseteq\Omega_1$. Thus $U^R(\boldsymbol{\theta}^2)\leq U^R(\boldsymbol{\theta}^1)$ (since $\boldsymbol{\theta}^1$ is being chosen from a larger set) and

$$\delta\left(U^R\left(\boldsymbol{\theta}^2\right)-V\right)\leq\delta\left(U^R\left(\boldsymbol{\theta}^1\right)-V\right).$$

From (V.3) it follows that H is strictly increasing on w and strictly decreasing with respect to c, therefore

$$\theta_{ij}^2=H\left(y_i,c_{ij}^2,\delta\left(U^R\left(\boldsymbol{\theta}^2\right)-V\right)\right)<H\left(y_i,c_{ij}^1,\delta\left(U^R\left(\boldsymbol{\theta}^1\right)-V\right)\right)=\theta_{ij}^1,$$

concluding the proof. Note that θ_{ij}^1 increases with respect to θ_{ij}^2 directly by the effect of c_{ij}^1, but also indirectly by effect on the utility level $U^R(\boldsymbol{\theta}^1)$.

Proof of Prediction 3. As in the previous prediction, let $c_{ij}^1<c_{ij}^2$ two different transaction cost. Let θ_{ij}^1 and θ_{ij}^2 the stationary relational contracts associated with each c_{ij}^1, c_{ij}^2, respectively. From Prediction 2, we know that $\theta_{ij}^1>\theta_{ij}^2$. Which means that as long as the first best allocation $\hat{\theta}$ is never achieved then

$$\theta_{ij}^1=H\left(y_i,c_{ij}^1,\delta\left(U^R\left(\boldsymbol{\theta}^1\right)-V\right)\right)>H\left(y_i,c_{ij}^2,\delta\left(U^R\left(\boldsymbol{\theta}^2\right)-V\right)\right)=\theta_{ij}^2.$$

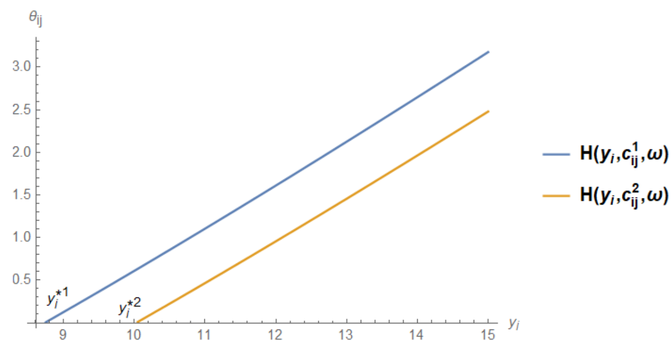
The previous inequality holds for any y_i that satisfies

$$f(y_i)+c_{ij}^1>\delta\left(U^R\left(\boldsymbol{\theta}^1\right)-V\right)>\delta\left(U^R\left(\boldsymbol{\theta}^2\right)-V\right),$$

recall that $U^R(\cdot)$ is increasing with respect to θ_{ij} by (V.6). Now let y_i^{*1} and y_i^{*2}

be the points such that $H\left(y_i^{*1}, c_{ij}^1, \delta\left(U^R(\mathbf{0}) - V\right)\right) = 0 = H\left(y_i^{*2}, c_{ij}^2, \delta\left(U^R(\mathbf{0}) - V\right)\right)$ (note that by (V.3) and continuity they must exists). Also note that H is strictly increasing with respect to y (see Prediction 1), which implies that $y_i^{*1} < y_i^{*2}$ (see Figure V.1).

Figure V.1: y_i^{*1} vs. y_i^{*2}



Proof of Prediction 4. The proof of this prediction follows from the proof of Proposition 2: we showed that $U_t^R(\{\boldsymbol{\theta}_t\}_t; \gamma_t)$ is strictly increasing with respect to γ_t. Then, an optimal dynamic relational contract must be monotonic, i.e. it satisfies $\theta_{ij,t}^* \leq \theta_{ij,t+1}^*$ for all $t \in \mathbb{N}$.

Proof of Prediction 5. From the proof of Proposition 2, $U_t^R(\{\boldsymbol{\theta}_t\}_t; \gamma_t)$ is strictly increasing with respect to γ_t and that an optimal dynamic relational contract must be monotonic. These two facts and equation (V.8) show that as the maturity of the relationship increases the frequency of transfers between i and j increase.

W Home line

For all units in the data, we take the longest time period for which we have recorded productivity data which is approximately 1 year. This way, the definition of home lines is not affected by the period we keep to construct the dyadic dataset. To define the workers' home line, we proceed as follows:

1. We break this period into trimesters and find on which line do workers spend the most days for each of those 3 months periods and take that line as the first approximation of their home line.

2. Then, we investigate whether a worker's home line changes across two trimesters. When it is the case, we look at which line this worker was working on around the trimester cutoff. If a worker is on her new home line a few days before the trimester cutoff, we update that worker's home line for those days to be the home line of the upcoming trimester rather than the home line of the current trimester (see Table W.1). We do a similar updating when a worker is working on her home line of the previous trimester a few days in the current trimester where her home line changes (see Table W.2). We carefully take into account days traded and days absent in this exercise.

Table W.1: First adjustment

	Trimester 1					Trimester 2				
Day of the trimester	n-4	n-3	n-2	n-1	n	1	2	3	4	5
Home line	1	1	1	1	1	2	2	2	2	2
Line where the worker is assigned	1	1	2	2	2	2	2	2	2	2
Updated home line	1	1	2	2	2	2	2	2	2	2

Table W.2: Second adjustment

	Trimester 1					Trimester 2				
Day of the trimester	n-4	n-3	n-2	n-1	n	1	2	3	4	5
Home line	1	1	1	1	1	2	2	2	2	2
Line where the worker is assigned	1	1	1	1	1	1	1	1	2	2
Updated home line	1	1	1	1	1	1	1	1	2	2

3. With this updated definition of home line for the workers, we find whether they spent more than or equal to 40% of the days they were present during a given trimester in a near consecutive way on a different line than their home line currently defined. When this is the case and the worker worked more than 20 days during this trimester, we update her home line for those consecutive days to be the line where she spent those days. When doing this exercise, we account for trades and days absent. Consider a case where a worker is present 80 days in a 3-month period. She spends 45 days on line 1. Therefore, line 1 is currently her home line given our definition. She spends 32 (40%) near consecutive days on line 2, but she is seen on line 3 three days in that period. Even if the 32 days were not consecutive, she was clearly assigned to line 2 over that period and was traded 3 days to line 3. Therefore, we update her home line over that period to be line 2 (see Table W.3). A similar adjustment is done if the worker is absent (see table W.4 where a indicates that the worker is absent). We, then, redo step 2 in case the adjustments done in step 3 were right at the cutoff of 2 trimesters.

Table W.3: Third adjustment

	Trimester 1														
Day of the trimester	1	2	3	4	5	6	7	8	...	32	33	34	35	...	80
Home line	1	1	1	1	1	1	1	1	...	1	1	1	1	...	1
Line where the worker is assigned	3	2	2	3	3	2	2	2	...	2	1	1	1	...	1
Updated home line	2	2	2	2	2	2	2	2	...	2	1	1	1	...	1

Table W.4: Fourth adjustment

	Trimester 1														
Day of the trimester	1	2	3	4	5	6	7	8	...	32	33	34	35	...	80
Home line	1	1	1	1	1	1	1	1	...	1	1	1	1	...	1
Line where the worker is assigned	a	2	2	a	a	2	2	2	...	2	1	1	1	...	1
Updated home line	2	2	2	2	2	2	2	2	...	2	1	1	1	...	1

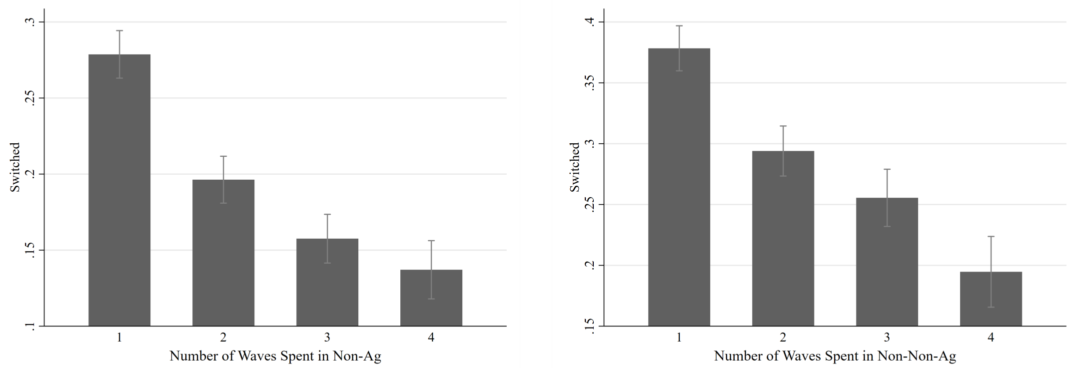
VII

Appendices for Chapter III: Learning, Selection, and the Misallocation of Households Across Sectors

X Appendix Figures

Figure X.1: Switching by Number of Waves Spent in Previous Sector: Non-Agricultural and Agricultural

A. Previous Sector Non-Agricultural   B. Previous Sector Agricultural



Notes: Sample consists of IFLS households with non-missing income information in all five waves of the IFLS. Error bars denote 95% confidence intervals.

Table X.1: Structural Estimates (Robustness)

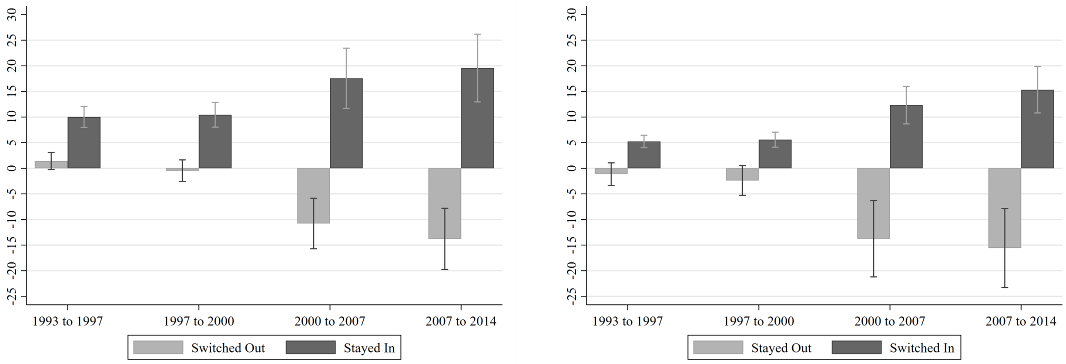
	Specification			
	(1)	(2)	(3)	(4)
	Baseline	Definition2	Definition3	Individual
β	3.91***	4.06***	5.68***	0.36***
	(0.40)	(0.39)	(0.37)	(0.04)
ϕ	-4.67***	-7.58	-4.67***	-3.90**
	(1.75)	(4.80)	(1.16)	(1.94)

Notes: Structural parameters estimated using minimum distance. Standard errors reported in parentheses. * p< 0.1 ** p< 0.05 *** p< 0.01. Column 1 reports estimates from the baseline model in Table 15, which defines non-agricultural households as those that own a non-agricultural enterprise or have any wage workers in the non-agricultural sector. Column 2 requires that non-agricultural households have a non-agricultural enterprise or at least half of the household working in the non-agricultural sector. Column 3 requires that non-agricultural households have a non-agricultural enterprise or earn least half of their income from non-agricultural wage work. Column 4 uses individual-level IFLS data from Hicks et al. (2017).

Figure X.2: Expected Returns by Switch Status, Wave, and Current Sector

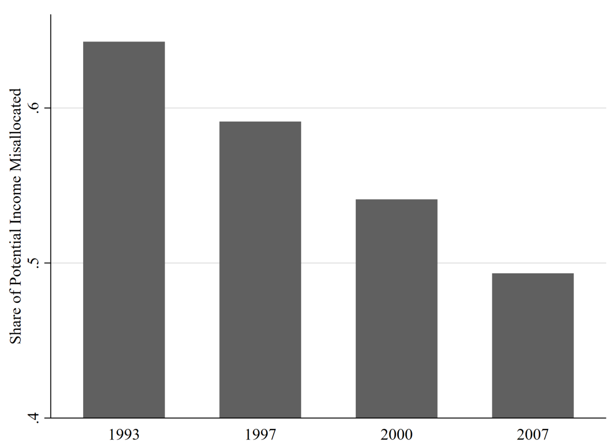
A. Non-Agricultural (in period t)

B. Agricultural (in period t)



Notes: The figure reports the average return to the non-agricultural sector ($\beta + \phi m_{it}$), separately for each transition, across all households in each category. "Stayed out" includes households in agriculture in both t and $t+1$. "Switched In" includes households in agriculture in t and the non-agricultural sector in $t+1$. "Switched Out" includes households in the non-agricultural sector in t and agriculture in $t+1$. "Stayed In" includes households in the non-agricultural sector in both t and $t+1$. Error bars denote 95% confidence intervals. Standard errors are calculated analytically (see Appendix Y.2).

Figure X.3: Share of Potential Income Misallocated



Notes: Misallocated income is defined as the absolute value of final returns ($\beta + m_{i4}$) among misallocated households). The share of potential income misallocated is equal to the sum of all misallocated income divided by the potential income (realized income plus final return) among misallocated households.

Y Additional Equations

Y.1 Minimum Distance Restrictions

The minimum distance restrictions are as follows.

$\gamma_1^1 = \beta + \phi\lambda_0 + \lambda_1 + \phi\lambda_1$

$\gamma_2^1 = \lambda_2$

$\gamma_3^1 = \lambda_3$

$\gamma_4^1 = \lambda_4$

$\gamma_5^1 = \lambda_5$

$\gamma_{12}^1 = \phi\lambda_2 + \lambda_{12} + \phi\lambda_{12}$

$\gamma_{13}^1 = \phi\lambda_3 + \lambda_{13} + \phi\lambda_{13}$

$\gamma_{14}^1 = \phi\lambda_4 + \lambda_{14} + \phi\lambda_{14}$

$\gamma_{15}^1 = \phi\lambda_5 + \lambda_{15} + \phi\lambda_{15}$

$\gamma_{23}^1 = \lambda_{23}$

$\gamma_{24}^1 = \lambda_{24}$

$\gamma_{25}^1 = \lambda_{25}$

$\gamma_{34}^1 = \lambda_{34}$

$\gamma_{35}^1 = \lambda_{35}$

$\gamma_{45}^1 = \lambda_{45}$

$$\gamma^1_{123} = \phi\lambda_{23} + \lambda_{123} + \phi\lambda_{123}$$

$$\gamma^1_{124} = \phi\lambda_{24} + \lambda_{124} + \phi\lambda_{124}$$

$$\gamma^1_{125} = \phi\lambda_{25} + \lambda_{125} + \phi\lambda_{125}$$

$$\gamma^1_{134} = \phi\lambda_{34} + \lambda_{134} + \phi\lambda_{134}$$

$$\gamma^1_{135} = \phi\lambda_{35} + \lambda_{135} + \phi\lambda_{135}$$

$$\gamma^1_{145} = \phi\lambda_{45} + \lambda_{145} + \phi\lambda_{145}$$

$$\gamma^1_{234} = \lambda_{234}$$

$$\gamma^1_{235} = \lambda_{235}$$

$$\gamma^1_{245} = \lambda_{245}$$

$$\gamma^1_{345} = \lambda_{345}$$

$$\gamma^1_{1234} = \phi\lambda_{234} + \lambda_{1234} + \phi\lambda_{1234}$$

$$\gamma^1_{1235} = \phi\lambda_{235} + \lambda_{1235} + \phi\lambda_{1235}$$

$$\gamma^1_{1245} = \phi\lambda_{245} + \lambda_{1245} + \phi\lambda_{1245}$$

$$\gamma^1_{1345} = \phi\lambda_{345} + \lambda_{1345} + \phi\lambda_{1345}$$

$$\gamma^1_{2345} = \lambda_{2345}$$

$$\gamma^1_{12345} = \phi\lambda_{2345} + \lambda_{12345} + \phi\lambda_{12345}$$

$$\gamma^2_1 = \lambda_1$$

$$\gamma^2_2 = \beta + \phi\theta_{20} + \theta_{22} + \phi\theta_{22} + \phi\lambda_0 + \lambda_2 + \phi\lambda_2$$

$$\gamma^2_3 = \theta_{23} + \lambda_3$$

$\gamma_4^2 = \theta_{24} + \lambda_4$

$\gamma_5^2 = \theta_{25} + \lambda_5$

$\gamma_{12}^2 = \phi\lambda_1 + \lambda_{12} + \phi\lambda_{12}$

$\gamma_{13}^2 = \lambda_{13}$

$\gamma_{14}^2 = \lambda_{14}$

$\gamma_{15}^2 = \lambda_{15}$

$\gamma_{23}^2 = \phi\theta_{23} + \phi\lambda_3 + \lambda_{23} + \phi\lambda_{23}$

$\gamma_{24}^2 = \phi\theta_{24} + \phi\lambda_4 + \lambda_{24} + \phi\lambda_{24}$

$\gamma_{25}^2 = \phi\theta_{25} + \phi\lambda_5 + \lambda_{25} + \phi\lambda_{25}$

$\gamma_{34}^2 = \lambda_{34}$

$\gamma_{35}^2 = \lambda_{35}$

$\gamma_{45}^2 = \lambda_{45}$

$\gamma_{123}^2 = \phi\lambda_{13} + \lambda_{123} + \phi\lambda_{123}$

$\gamma_{124}^2 = \phi\lambda_{14} + \lambda_{124} + \phi\lambda_{124}$

$\gamma_{125}^2 = \phi\lambda_{15} + \lambda_{125} + \phi\lambda_{125}$

$\gamma_{134}^2 = \lambda_{134}$

$\gamma_{135}^2 = \lambda_{135}$

$\gamma_{145}^2 = \lambda_{145}$

$\gamma_{234}^2 = \phi\lambda_{34} + \lambda_{234} + \phi\lambda_{234}$

$$\gamma^2_{235} = \phi\lambda_{35} + \lambda_{235} + \phi\lambda_{235}$$

$$\gamma^2_{245} = \phi\lambda_{45} + \lambda_{245} + \phi\lambda_{245}$$

$$\gamma^2_{345} = \lambda_{345}$$

$$\gamma^2_{1234} = \phi\lambda_{134} + \lambda_{1234} + \phi\lambda_{1234}$$

$$\gamma^2_{1235} = \phi\lambda_{135} + \lambda_{1235} + \phi\lambda_{1235}$$

$$\gamma^2_{1245} = \phi\lambda_{145} + \lambda_{1245} + \phi\lambda_{1245}$$

$$\gamma^2_{1345} = \lambda_{1345}$$

$$\gamma^2_{2345} = \phi\lambda_{345} + \lambda_{2345} + \phi\lambda_{2345}$$

$$\gamma^2_{12345} = \phi\lambda_{1345} + \lambda_{12345} + \phi\lambda_{12345}$$

$$\gamma^3_{1} = \lambda_{1}$$

$$\gamma^3_{2} = \lambda_{2}$$

$$\gamma^3_{3} = \beta + \phi\theta_{30} + \theta_{33} + \phi\theta_{33} + \phi\lambda_0 + \lambda_3 + \phi\lambda_3$$

$$\gamma^3_{4} = \theta_{34} + \lambda_{4}$$

$$\gamma^3_{5} = \theta_{35} + \lambda_{5}$$

$$\gamma^3_{12} = \lambda_{12}$$

$$\gamma^3_{13} = \phi\lambda_1 + \lambda_{13} + \phi\lambda_{13}$$

$$\gamma^3_{14} = \lambda_{14}$$

$$\gamma^3_{15} = \lambda_{15}$$

$$\gamma^3_{23} = \phi\lambda_2 + \lambda_{23} + \phi\lambda_{23}$$

$\gamma^3_{24} = \lambda_{24}$

$\gamma^3_{25} = \lambda_{25}$

$\gamma^3_{34} = \phi\theta_{34} + \phi\lambda_4 + \lambda_{34} + \phi\lambda_{34}$

$\gamma^3_{35} = \phi\theta_{35} + \phi\lambda_5 + \lambda_{35} + \phi\lambda_{35}$

$\gamma^3_{45} = \lambda_{45}$

$\gamma^3_{123} = \phi\lambda_{12} + \lambda_{123} + \phi\lambda_{123}$

$\gamma^3_{124} = \lambda_{124}$

$\gamma^3_{125} = \lambda_{125}$

$\gamma^3_{134} = \phi\lambda_{14} + \lambda_{134} + \phi\lambda_{134}$

$\gamma^3_{135} = \phi\lambda_{15} + \lambda_{135} + \phi\lambda_{135}$

$\gamma^3_{145} = \lambda_{145}$

$\gamma^3_{234} = \phi\lambda_{24} + \lambda_{234} + \phi\lambda_{234}$

$\gamma^3_{235} = \phi\lambda_{25} + \lambda_{235} + \phi\lambda_{235}$

$\gamma^3_{245} = \lambda_{245}$

$\gamma^3_{345} = \phi\lambda_{45} + \lambda_{345} + \phi\lambda_{345}$

$\gamma^3_{1234} = \phi\lambda_{124} + \lambda_{1234} + \phi\lambda_{1234}$

$\gamma^3_{1235} = \phi\lambda_{125} + \lambda_{1235} + \phi\lambda_{1235}$

$\gamma^3_{1245} = \lambda_{1245}$

$\gamma^3_{1345} = \phi\lambda_{145} + \lambda_{1345} + \phi\lambda_{1345}$

$$\gamma^3_{2345} = \phi\lambda_{245} + \lambda_{2345} + \phi\lambda_{2345}$$

$$\gamma^3_{12345} = \phi\lambda_{1245} + \lambda_{12345} + \phi\lambda_{12345}$$

$$\gamma^4_1 = \lambda_1$$

$$\gamma^4_2 = \lambda_2$$

$$\gamma^4_3 = \lambda_3$$

$$\gamma^4_4 = \beta + \phi\theta_{40} + \theta_{44} + \phi\theta_{44} + \phi\lambda_0 + \lambda_4 + \phi\lambda_4$$

$$\gamma^4_5 = \theta_{45} + \lambda_5$$

$$\gamma^4_{12} = \lambda_{12}$$

$$\gamma^4_{13} = \lambda_{13}$$

$$\gamma^4_{14} = \phi\lambda_1 + \lambda_{14} + \phi\lambda_{14}$$

$$\gamma^4_{15} = \lambda_{15}$$

$$\gamma^4_{23} = \lambda_{23}$$

$$\gamma^4_{24} = \phi\lambda_2 + \lambda_{24} + \phi\lambda_{24}$$

$$\gamma^4_{25} = \lambda_{25}$$

$$\gamma^4_{34} = \phi\lambda_3 + \lambda_{34} + \phi\lambda_{34}$$

$$\gamma^4_{35} = \lambda_{35}$$

$$\gamma^4_{45} = \phi\theta_{45} + \phi\lambda_5 + \lambda_{45} + \phi\lambda_{45}$$

$$\gamma^4_{123} = \lambda_{123}$$

$$\gamma^4_{124} = \phi\lambda_{12} + \lambda_{124} + \phi\lambda_{124}$$

$$\gamma^4_{125} = \lambda_{125}$$

$$\gamma^4_{134} = \phi\lambda_{13} + \lambda_{134} + \phi\lambda_{134}$$

$$\gamma^4_{135} = \lambda_{135}$$

$$\gamma^4_{145} = \phi\lambda_{15} + \lambda_{145} + \phi\lambda_{145}$$

$$\gamma^4_{234} = \phi\lambda_{23} + \lambda_{234} + \phi\lambda_{234}$$

$$\gamma^4_{235} = \lambda_{235}$$

$$\gamma^4_{245} = \phi\lambda_{25} + \lambda_{245} + \phi\lambda_{245}$$

$$\gamma^4_{345} = \phi\lambda_{35} + \lambda_{345} + \phi\lambda_{345}$$

$$\gamma^4_{1234} = \phi\lambda_{123} + \lambda_{1234} + \phi\lambda_{1234}$$

$$\gamma^4_{1235} = \lambda_{1235}$$

$$\gamma^4_{1245} = \phi\lambda_{125} + \lambda_{1245} + \phi\lambda_{1245}$$

$$\gamma^4_{1345} = \phi\lambda_{135} + \lambda_{1345} + \phi\lambda_{1345}$$

$$\gamma^4_{2345} = \phi\lambda_{235} + \lambda_{2345} + \phi\lambda_{2345}$$

$$\gamma^4_{12345} = \phi\lambda_{2345} + \lambda_{12345} + \phi\lambda_{12345}$$

$$\gamma^5_{1} = \lambda_{1}$$

$$\gamma^5_{2} = \lambda_{2}$$

$$\gamma^5_{3} = \lambda_{3}$$

$$\gamma^5_{4} = \lambda_{4}$$

$$\gamma^5_{5} = \beta + \phi\theta_{50} + \theta_{55} + \phi\theta_{55} + \phi\lambda_{0} + \lambda_{5} + \phi\lambda_{5}$$

$$\gamma^5_{12} = \lambda_{12}$$

$$\gamma^5_{13} = \lambda_{13}$$

$$\gamma^5_{14} = \lambda_{14}$$

$$\gamma^5_{15} = \phi\lambda_1 + \lambda_{15} + \phi\lambda_{15}$$

$$\gamma^5_{23} = \lambda_{23}$$

$$\gamma^5_{24} = \lambda_{24}$$

$$\gamma^5_{25} = \phi\lambda_2 + \lambda_{25} + \phi\lambda_{25}$$

$$\gamma^5_{34} = \lambda_{34}$$

$$\gamma^5_{35} = \phi\lambda_3 + \lambda_{35} + \phi\lambda_{35}$$

$$\gamma^5_{45} = \phi\lambda_4 + \lambda_{45} + \phi\lambda_{45}$$

$$\gamma^5_{123} = \lambda_{123}$$

$$\gamma^5_{124} = \lambda_{124}$$

$$\gamma^5_{125} = \phi\lambda_{12} + \lambda_{125} + \phi\lambda_{125}$$

$$\gamma^5_{134} = \lambda_{134}$$

$$\gamma^5_{135} = \phi\lambda_{13} + \lambda_{135} + \phi\lambda_{135}$$

$$\gamma^5_{145} = \phi\lambda_{14} + \lambda_{145} + \phi\lambda_{145}$$

$$\gamma^5_{234} = \lambda_{234}$$

$$\gamma^5_{235} = \phi\lambda_{23} + \lambda_{235} + \phi\lambda_{235}$$

$$\gamma^5_{245} = \phi\lambda_{24} + \lambda_{245} + \phi\lambda_{245}$$

$$\gamma^5_{345} = \phi\lambda_{34} + \lambda_{345} + \phi\lambda_{345}$$

$$\gamma^5_{1234} = \lambda_{1234}$$

$$\gamma^5_{1235} = \phi\lambda_{123} + \lambda_{1235} + \phi\lambda_{1235}$$

$$\gamma^5_{1245} = \phi\lambda_{124} + \lambda_{1245} + \phi\lambda_{1245}$$

$$\gamma^5_{1345} = \phi\lambda_{134} + \lambda_{1345} + \phi\lambda_{1345}$$

$$\gamma^5_{2345} = \phi\lambda_{234} + \lambda_{2345} + \phi\lambda_{2345}$$

$$\gamma^5_{12345} = \phi\lambda_{1234} + \lambda_{12345} + \phi\lambda_{12345}$$

Y.2 Standard Errors

In Figures 20 and X.2, we report error bars for average returns ($\beta + \phi m_{it}$) across various combinations of household types and waves. In this section, we describe how we obtain the required standard errors.

We denote estimated average returns for a particular group of households in a particular wave as $\hat{f}$. To estimate $\hat{f}$, we use estimates of the parameters β, ϕ, and some combination of the λ and θ parameters that are required to estimate m_{it}. In short, $\hat{f}$ is a non-linear function of estimated parameters and household decisions D_{it}. We define

$$\hat{f} = \frac{1}{N} \sum_{i=1}^{A} h(X_i, \hat{\rho}),$$

where $\hat{\rho}$ represents a vector of the estimated structural parameters, X_i is vector of household i's sectoral decisions, and $h(.)$ is a continuous and differentiable function. We can define $\tilde{f}$ as the sample average return calculated using the true parameter vector (ρ_0):

$$\tilde{f} = \frac{1}{N} \sum_{i=1}^{A} h(X_i, \rho_0),$$

and the population average return as

$$f = E[h(X, \rho_0)],$$

where the expectation is over the joint distribution of X.

If we decompose the difference between the estimated $\hat{f}$ and the population parameter f into two parts:

$$(\hat{f} - f) = (\hat{f} - \tilde{f}) + (\tilde{f} - f),$$

then it can be shown that the variance of $(\hat{f} - f)$ is the sum of two terms: the variance of $(\tilde{f} - f)$ and $(\hat{f} - \tilde{f})$ (See Molina (2016) for details). Specifically,

$$\mathrm{Var}(\hat{f} - f) = \frac{\sigma^2}{N} + \frac{s^2}{N},$$

where (using the delta method)

$$\frac{\sigma^2}{N} = \frac{1}{N} E\left[\nabla h(\rho_0)\right]' V E\left[\nabla h(\rho_0)\right]$$

and

$$\frac{s^2}{N} = \frac{1}{N} \mathrm{Var}(h(X, \rho_0)).$$

Z Data Appendix

Z.1 Selecting Household Characteristics

As described in section 17.3, we use lasso to select a set of household-level predictors of returns to the non-agricultural sector from a wide range of variables. Below, we describe all 27 variables included in the lasso.

- Years of educational attainment (average and maximum): We calculate both average and maximum educational attainment across all household members.
- Raven's test z-score (average and maximum): The IFLS administered a test of cognitive ability (which included questions from the Raven's test of fluid intelligence as well as a few math questions). Different versions of the test were given to respondents aged 7-14 and 15-59. We calculate the version-specific z-score for each respondent and average across all household members. We also calculate the maximum.
- Risk aversion score (average and maximum): This is a five-point score generated from a set of five questions asked of those aged 15 and older, where a score of 5 represents the highest level of risk aversion. Each question offers two hypothetical options: receiving 4 million rupiah for certain, or a lottery with a higher expected value. We calculate the average and maximum score across all household members.
- Height (average and maximum): The IFLS measures height for all household members. Restricting to adults aged 20-65, we standardize height separately for men and women. We calculate the average and maximum z-score across all adults.

- Self-reported health (average and maximum): All respondents aged 15 and older are asked whether they consider themselves very healthy, somewhat healthy, somewhat unhealthy, or unhealthy. We assign a 4 to very healthy and 1 to unhealthy, and calculate both the average and maximum.

- Share of very healthy adults: We calculate the share of household members aged 15 and older who consider themselves very healthy.

- Share of somewhat healthy adults: We calculate the share of household members aged 15 and older who consider themselves very healthy or somewhat healthy.

- Physical functioning (average and maximum): The IFLS asks all respondents aged 15 and older whether they can easily, can with difficulty, or cannot at all do 23 physical activity tasks (including activities of daily living, instrumental activities of daily living, and other physical tasks). We calculate the share of activities a respondent "can easily" do. We then calculate the average share and maximum share for each household.

- Mental health score (average and maximum): To measure mental health (for respondents aged 15 and older), the IFLS includes a 10-question version of the CES-D questionnaire designed to help identify clinical depression. We sum the responses to all 10 questions, which generates a score ranging from 0 to 30 points, where higher numbers are associated with a higher severity of depressive symptoms. We calculate the average and maximum score for each household.

- Share of members with depressive symptoms: Using the 10-question CES-D questionnaire described above, we calculate the share of (adult) household members with a score of 10 or greater, a cutoff that is used as an indicator of significant depressive symptoms (Zhang et al., 2012).

- Big 5 personality traits (open-mindedness, conscientiousness, extraversion, agreeableness, negative emotionality – average and maximum): The IFLS includes the Big Five Index 15 (BFI 15), a set of 15 questions about the respondents' personality, three for each of the five personality traits. We use these to create a five-point score for each of the five personality traits. We calculate the average and maximum score for each household, for each of the five personality traits.